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Dynamic route choice in hurricane evacuation

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DYNAMIC ROUTE CHOICE IN HURRICANE EVACUATION

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To

Sajjad,

Ali the oldest,

Ali the youngest

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ABSTRACT

In this research a framework is developed for modeling route choice in hurricane evacuation. Two behavioral hypotheses are evaluated which together with the route choice model, constitute the contributions of the research. The first hypothesis states that beside congestion, other variables such as familiarity with the route, availability of fuel and shelter, facility class, and length of route have an effect on an evacuees' route choice. The second hypothesis states that as time passes and storm conditions change, the impact each variable has on route choice changes. The logit structure was used for modeling the choice process and stated choice data previously collected from the New Orleans area on hypothetical storms was used to calibrate the model. The study found that accessibility of a route, familiarity with a route, facility class, length of a route, and availability of services (gas stations and hotels) had an effect on evacuation route choice. The magnitude of the coefficients of perceived service, accessibility, and distance differed among those evacuating in the first half of the evacuation period versus those that evacuated in the second half but coefficients of facility class were not significantly different between two time intervals. Observed traffic count data from hurricane Katrina evacuation was used to validate the model. Comparison of traffic volumes predicted by the model with actual traffic volumes from hurricane Katrina shows error percentages of 17.5, 0.01, and 28 percent of error for volumes on I-10, I-55, and US-61 respectively.

Chapter 1 Introduction

1.1. Background

Evacuation is a common response against natural and man-made disasters threatening an area. From a strategic point of view, an apparent trend of increasing frequency and intensity of natural disasters over the past several decades (Newkirk, 2001) and the discrepancy between population growth in coastal areas and infrastructure capacity to safely evacuate them (Plowman, 2001), are challenges facing evacuation management. On the other hand, modeling and computational advances and the experience and behavioral data gained from each evacuation operation are an increasing asset at the disposal of experts.

Despite the general perception, evacuation is not necessarily combined with panic and disorder. Therefore, evacuation behavior is typically not haphazard or chaotic and rational behavioral patterns are observed. This rationality is assumed in forecasts, and in the preparation for and administration of the evacuation process. New evacuation modeling procedures are in the process of being developed which will lead to prediction of network conditions under different conditions assuming rational response from respondents (Fu, 2004; Cheng, 2010).

Several aspects of evacuation modeling are similar to those applied in urban travel demand modeling including modeling travel in discrete sequential steps of trip generation, estimation of departure times, destination choice, and trip assignment. The evacuation planning process is analogous to the classical four-step transportation planning process except in the use of trip purposes and also a slight difference in the use of mode choice. Commonly, households possessing a vehicle are assumed to use it as their mode of evacuation and public transportation is used by “captives”. The hurricane evacuation modeling process can be described as the sequence of activities shown in Figure 1.1.

Fu (2004) developed a dynamic travel demand model and Cheng (2010) developed a dynamic trip distribution model for hurricane evacuation. Naghawi (2010) used microsimulation to model transit-based emergency evacuation. The research reported in this dissertation is concerned with modeling route choice under hurricane evacuation conditions. Dynamic origin destination matrices, aggregate specification of the routes available for evacuation, and the hurricane characteristics are inputs to the model while dynamic traffic volume on each route is the output.

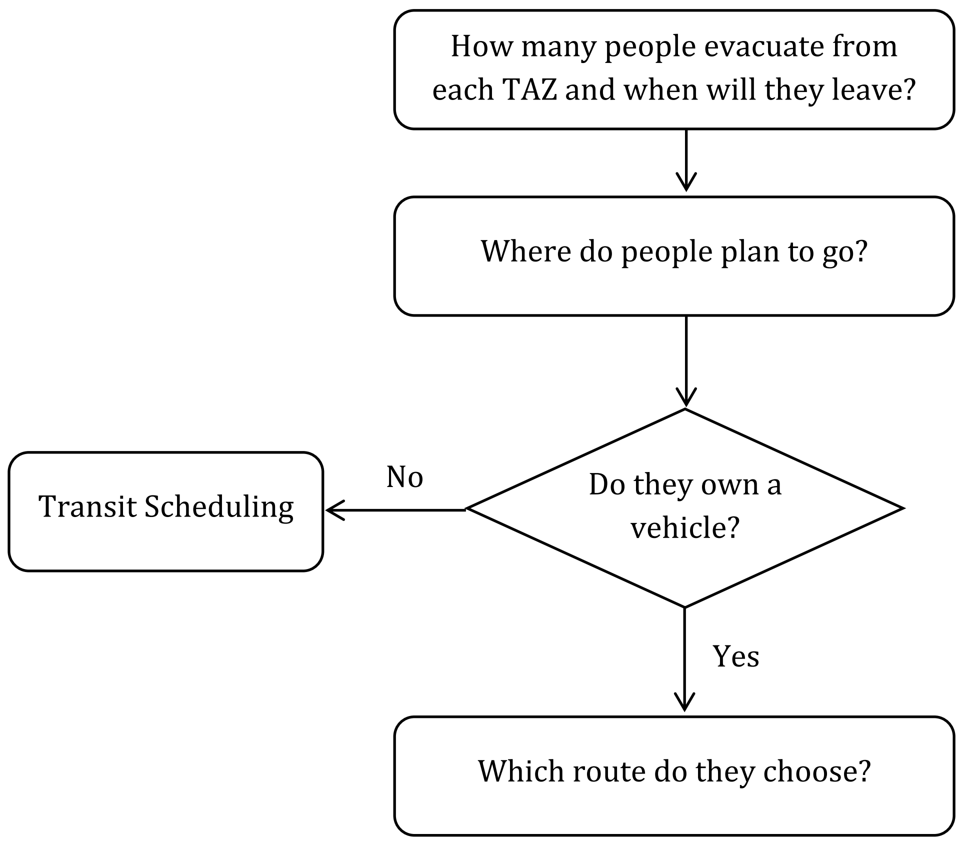

Figure 1.1: Hurricane Evacuation Planning

1.2. Research Objectives

Based on a review of current practice, this research aims at making two contributions to the body of knowledge in the area of evacuation assignment as discussed in the following sections.

1.2.1. Relevant Variables for Route Choice

Hypothesis: There are more factors than just travel time that have a significant influence on route choice in hurricane evacuation.

Most route choice models in urban transportation planning consider travel time as the main determinant of route choice. For commuters especially, travel time reliability, travel monetary cost, and late/early arrival penalties are included in some research but are generally not included in urban route assignment models. In evacuation assignment, travel time has typically also been the sole criterion on which route assignment has been based in the past but emergency conditions may make this sole factor inadequate in accurately portraying evacuation behavior. Instead, other attributes such as storm characteristics or features of the route are, intuitively, expected to play a greater role in an evacuation trip. For example, there might be preferences towards some facility classes such as interstate highways versus lower-level roads. Dow and Cutter (2002) state that during evacuation from hurricane Floyd, evacuees displayed a preference for the interstate system and many travelers decided to stay on it despite the congestion that developed as a result. Besides freeway bias, Chiu and Mirchandani (2008) argue that there is a tendency towards using familiar routes in evacuation route choice. Although this tendency might be ascribed to higher perceived reliability of these roads, the effect of familiarity as a variable should be tested for inclusion in route choice during evacuation.

Brown et al. (2009) state that during hurricane Rita evacuation in 2005, many travelers were stuck on major evacuation routes for up to 18 hours, and this resulted in vehicles running out of gas and obstructing the normal flow of traffic. Moreover, retrospective data collected in 2009 by Gudishala as part of his PhD dissertation showed that more than ten percent of the respondents mentioned finding a restroom as a difficulty they had experienced during their evacuation from hurricane Gustav in 2008, and a slightly higher percentage mentioned the need for food as a difficulty they experienced. Travelers aware of these facts may prefer a route with a gas station and amenities (i.e. a high level of commercial development) along the road.

Another factor that is likely to play a role in route choice during evacuation from a hurricane is whether a route will be subjected to storm conditions. Hypothetically, when an evacuee has a choice among two or more routes, the choice is likely to be the one furthest from the hurricane's projected path or at least not one that could experience gale force or heavy rainfall conditions during the evacuation process.

It is also probable that at the time of evacuation, accessibility to a route will affect the probability of selecting it. Intuitively, in extreme situations people select the route which is the most accessible from their residence and use it to get away from danger as quickly as possible. Distance from home to a route can be used as a proxy for accessibility to that route.

1.2.2. Time Dependency of Variables

Hypothesis: The importance of factors affecting route choice change over time.

The importance of some variables may vary depending on time-related factors such as the proximity of a disaster. For instance, travel time to a safe destination is likely to become less important as a hurricane gets closer to an individual because the urgency is higher and the desire is to get to safety with less consideration of cost. This suggests behavioral differences between early evacuees and late evacuees and this in turn implies time dependency of parameters in the model. Besides the value of model parameters, their statistical significance may also be influenced by the dynamics of the disaster and some variables may become statistically insignificant in certain stages of the evacuation.

Time dependency of the model parameters would imply changes in route selection over time. As an extreme example, one route may be congested at the early stages of an evacuation while another route becomes congested at a later stage because evacuees value the features of one route in the early stages of the evacuation and the features of another route in the later stages of evacuation.

In the following chapters, the state of the practice in dynamic traffic assignment is first described. Then a description of the data used in the calibration of the route choice model developed in this study is provided. The process undertaken in data preparation is also explained. Then in the methodology chapter, the model structure, model details, and calibration and validation methods are explained and, finally, in the fifth chapter the results and conclusions of this research are presented.

Chapter 2 Literature Review

Dynamic Traffic Assignment (DTA) is the modeling of time varying flows on time varying road networks consistent with established traffic flow and travel demand theories. DTA is the dominant paradigm in dynamic network modeling. Thus, this review is mainly directed at DTA structures and methods.

Although route choice is only part of the traffic assignment process, other parts are also discussed and their state of the practice are explained in order to yield a more comprehensive view of the whole assignment framework and the interaction among its components. Moreover, the review is not confined to methods applied in the evacuation context only. In the sections which follow, the structure of DTA is presented, a description of its components is provided, and then current practice is described. Finally, criteria considered in route selection are discussed.

2.1 DTA Structure

According to the classic transportation planning process, people initially decide on making a trip (or evacuate in our particular case) and then select their destination. It is further assumed that selection among available travel modes is done after this and, finally, the "best" or "satisfactory" route connecting the origin to the destination is selected. Departure time choice is also sometimes included within the trip generation or trip assignment stages of the process. While this paradigm may not reflect actual behavior in either an urban transportation planning or evacuation context, it is commonly adopted for convenience since it breaks down the complex trip-making process into manageable subtasks.

Generally, attributes of the traveler, the trip, and available alternatives together with the traveler's information and perception of the network condition, affect the outcome of the choice process. Route choice models usually include some of these attributes as their variables.

In the context of traffic assignment, the interaction among link flows and link costs determine the level of service throughout the network. In order to capture this interaction, DTA models include a network loading and a route choice model that interact as shown in

Figure 2.1. The upper part of the diagram shows how route costs determine route flows through a route choice model. Then as the lower part of the diagram shows, flows are processed with individual link characteristics in the network loading model to produce link and, ultimately, route costs. Network loading and route choice models are described in greater detail in sections 2.2 and 2.3.

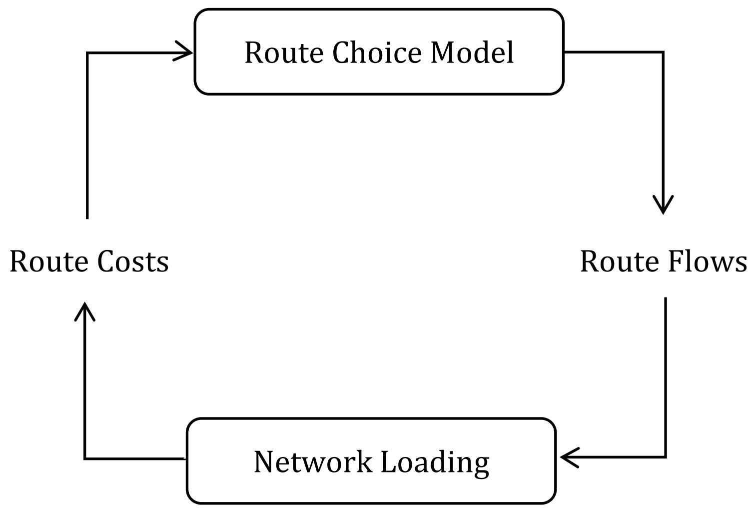

Figure 2.1: DTA model structure

2.2 Route Choice Models

Dynamic route choice models take time-dependent travel costs as input and yield time dependent link flows as their output. These models can be classified based on assumptions made on information availability and travelers reaction to traffic conditions, or, alternatively, on the formulation adopted in modeling the choice process. Based on a set of assumptions on information availability and travelers' reactions to the information they receive, route choice models can be further divided into pre-trip, en route, and hybrid classes.

Pre-trip models, also known as “non-adaptive” models, assume that travelers have perfect knowledge of travel cost on all routes and select their route at the origin and do not deviate from their selected path during the trip (Florian et al., 2008). The chosen routes may not turn out to be the most attractive ones when the resulting traffic conditions change from the initially predicted traffic conditions on which route choice was based. Therefore, an iterative procedure is typically employed to allow travelers to alter their route in each iteration, based on the experienced route costs. Repeating this process over a sufficiently large number of iterations leads to an equilibrium state (Pel et al., 2011).

En route models, also known as "reactive" or "adaptive" models, apply to cases in which travelers are assumed to have information on current traffic conditions only i.e. travelers display reactive rather than anticipatory behavior (Pel et al., 2009). Travelers may receive information at discrete points in time (e.g. radio broadcasts), discrete points in space (e.g. variable message signs), or continuously in both space and time (e.g. traffic conditions visible to the driver) (Florian et al., 2008).

Hybrid models combine features of pre-trip and en route models and assume that travelers choose their route at the origin based on perceived conditions at that time but may alter their route choice in response to changing conditions such as congestion and link availability.

2.2.1. Route Choice Process

Based on how they formulate the preference travelers have to alternatives, route choice models can be categorized as utility-based and non-utility-based models. These groups are explained in the following sections.

2.2.1.1. Utility-Based Models

Utility-based models establish a utility function for each route and assume that the travelers select the route that maximizes their expected utility. The utility function is assumed to consist of a deterministic and a stochastic part. The deterministic part is considered to be a function of measurable factors believed to have a significant effect on the attractiveness of a route e.g. travel time and cost. The stochastic part is assumed to incorporate the effect of unobserved attributes, unobserved taste variations, measurement errors, and the effect of including proxy variables within the utility function(Ben-Akiva and Lerman, 1985).

Discrete choice models are often used to apply the utility maximization assumption in route choice. Prato (2009) categorizes discrete route choice models into Logit, GEV (Generalized Extreme Value distribution), and Non-GEV structures based upon assumptions made on the distribution of the stochastic part of the utility function.

The logit model is derived under the assumption that the stochastic term of the utility function is independently and identically distributed (iid) with an extreme value distribution for all travelers. The iid assumption requires that the stochastic terms are uncorrelated over alternative routes, and have the same variance for all routes. Consequently, modifications of the logit model have been developed that preserve the logit structure but introduce a correction term within the deterministic part of their utility function to accommodate the correlation among alternatives arising from route overlaps. Models of this type include C-Logit, Path Size Logit, and Path Size Correction Logit (Prato, 2009).

As the name suggests, GEV models are based on a generalization of the extreme value distribution of the stochastic term. The generalization can take many forms, but a common element is that it allows correlation in unobserved variables over alternatives and collapses to the logit model when this correlation is zero (Train, 2009). The GEV group includes the Paired Combinatorial Logit model, Cross Nested Logit model, and the Generalized Nested Logit model (Prato, 2009).

Non-GEV model structures assume non-GEV distributions for the random term of the utility function and allow random taste variation and correlation in unobserved factors over time. Non-GEV group includes Multinomial Probit, Logit Kernel with Random Coefficients (also known as Mixed Logit), and Logit Kernel with a Factor Analytic Approach. Non-GEV models do not present a closed-form expression for the choice probabilities and simulated maximum likelihood is required for their estimation (Prato, 2009).

Selection among the three types of discrete choice models is a trade-off between ease of use and rigor. Logit models have the simplest but most restrictive functional form, GEV models have a more complicated but less restrictive formulation, and non-GEV models are the least restrictive but require more effort to estimate. While some non-GEV models are highly flexible, logit models are by far the most widely used discrete choice models (Train, 2009) although not necessarily in the area of route choice.

2.2.1.2 Non-Utility-based Models

There are certain aspects of the utility maximizing model that make it far from realistic. Firstly, typical utility functions are compensatory i.e. a good score in one attribute can compensate for a weak score in another, a condition that is not necessarily true in the evacuation context. For example, a low safety level of a road may not be compensated by its short travel time. Semi- and non-compensatory models are proposed to address this issue of which three are discussed in the following paragraphs.

Opasanon and Miller-Hooks (2006) applied the Pareto optimality concept in multicriteria adaptive route choice for stochastic time-dependent networks. In this method, routes are compared with each other based on all attributes of interest. A route is Pareto-optimal if it is as good as any other alternative in all attributes and better in at least one attribute i.e. it is not dominated. This model is a non-compensatory model as weakness in any attribute would prevent a route from being selected as the dominant alternative.

Chorus et al. (2008) employed the Random Regret Minimization (RRM) principle which presumes travelers base their choice on their desire to avoid the situation where a non-chosen route turns out to be more attractive than the chosen one, thereby causing regret. To apply the regret theory into travelers' choice, every attribute of an alternative is compared to its counterpart from the other alternatives and the regret that a traveler associates with a considered alternative equals the regret associated with the comparison of that alternative with the best of the other two alternatives. If an attribute of an alternative is equal to the best value, the resulting regret would be equal to 0. Each of the binary regrets among alternatives is a sum of the regrets associated with comparing the alternatives on an attribute by attribute basis.

By denoting an evaluated regret as R, alternatives as i, j, k,… and attributes as x, y, z,… Equation 2.1 presents an example of the attribute-regret functions (φ) proposed by Loomes and Sugden (1982). Parameters β are estimated from observed data.

$$\varphi_x(x_i, x_j) = \max\{0, \beta_x . (x_j - x_i)\} \tag{2.1}$$

$$R_{ij} = \varphi_x(x_i, x_j) + \varphi_y(y_i, y_j) + \varphi_z(z_i, z_j) + \cdots \tag{2.2}$$

$$R_i = \max\{R_{ij}, R_{ik}, \dots\} \tag{2.3}$$

The model assumes that the analyst is unable to exactly assess a traveler's intrinsic preference β_x for some routes over others. Hence an error term is added to the model denoted as η_n and it is assumed that it is normally distributed, $N(0,\sigma_z)$, which yields the probability of traveler n selecting route i to be:

$$P_n(i) = \int \left(\frac{\exp(-R_{in}(\eta_n)}{\sum_{l \in i,j,k} \exp(-R_{ln}(\eta_n))} \right) f(\eta_n) d\eta_n \tag{2.4}$$

Cantillo and Ortúzar (2005) proposed a semi-compensatory choice model which was based on the assumption that an individual has a certain "threshold of acceptance" for each attribute of an alternative and would not select that alternative if at least one of its attributes is beyond the threshold. Further, if more than one alternative survives the threshold test on all attributes, the individual will select the alternative that maximizes his utility.

The model assumes the thresholds to be random variables and in the first step forms a choice set for every individual by formulating the probability of alternative Ai being within the boundary of acceptance. In the second step, a compensatory choice process is performed in which a linear utility function is calibrated. The model diminishes to a traditional discrete choice model if the means of each threshold are large enough and their variances are small which practically means no threshold exists (Cantillo and Ortúzar, 2005).

An aspect of a typical utility function that may not always be desirable is that the absolute value of the change in utility is the same for an equal increase or decrease of a variable.

That is, $\frac{\partial U}{\partial x_i} = \beta_i$ where xi is a variable and β_i is its coefficient in the utility function U. However, the disutility of an increase in travel time resulting in being, for example, late for work, is not equal to the utility of arriving early by the same amount of time. The cumulative prospect model (Xu et al., 2011) addresses this issue by developing asymmetrical payoff functions. In order to calculate the payoff, a reference point is defined for every attribute of a route and the value of the attribute is perceived as either gain (for values better than the reference point) or loss (for values worse than the reference point). The amount of the payoff is then determined using an asymmetric value function. Route choice is then assumed to be a function of the weighted average of these payoffs. In calculating the weights, the model assumes that travelers are more concerned about the unlikely outcomes (e.g. travel times much longer or shorter than expected), and hence it assigns weights to the possible values of variables based on their cumulative probability of occurrence where the unlikely outcomes are overweighted and likely outcomes are underweighted.

The stochastic nature of traffic flow and the non-linear characteristics of traffic dynamics have also been tackled by employing methods of soft computing such as fuzzy logic and artificial neural networks (ANN). Fuzzy-based methods, including rule base and ranking approaches, have focused on the uncertainty and qualitative nature of traveler's perceptions of route attributes. The rule-based approach is used to determine the fuzzy cost level or travel time of a specific route, while the fuzzy ranking approach is employed to determine the choice among available alternatives (Rilett and Park, 2001, Ridwan, 2004). ANN methods on the other hand, have focused on addressing the nonlinearities existing in the choice process. Karlaftis and Vlahogianni (2010) give a thorough discussion on the application of neural networks in transportation research and their analogy to statistical methods applied in this field.

2.3 Network Loading Models

Network loading models use link flows to compute link travel times. In other words, they describe how, over time, traffic propagates along routes connecting origin-destination (OD) pairs. Traffic performance models and traffic flow models are the other names given to these models in the literature. Several network loading models are described in the following paragraphs.

”Whole link” traffic performance assumes the traveler experiences uniform conditions along the entire link. One group of whole link models, which are called link delay models, formulate link traversal time as a function of the number of vehicles existing on the link. Another group, called link exit function models, express outflow from a link as a function of the number of vehicles existing on the link. The final group, advanced exit function models, are similar to exit function models but consider a link storage capacity to capture the effects of physical queues like queue spillback (Szeto, 2008, Nie and Zhang, 2010).

The “queuing traffic performance model”, also known as the “bottleneck model”, considers each link in the network to have a flow-invariant travel time, and a point queue at its downstream end being discharged at a maximum service rate. When a traffic queue exists, the link outflow is equal to the capacity of the link and all travelers arriving before the queue dissipates incur travel delay. Otherwise, the outflow is taken as the inflow at the time of entry and the travelers are unimpeded (Chow, 2009). Time spent in the queue for vehicles is computed as the ratio of the number of vehicles on the link at the time the vehicle entered the link, over the queue discharge rate (Han, 2003 and 2007).

The “divided travel time model”, developed by Mun (2002), is similar to the queuing model but the difference is that the queue time for vehicles is computed based on the time they reach the back of the queue at the end of the link. Therefore, these models can be seen as a combination of the deterministic queuing model and the whole link traffic model.

The “wave model” is also referred to as the LWR (Lighthill, Witham, Richards) hydro-dynamic or fluid flow model. This model assumes a one-to-one relation between speed and density and, accordingly, formulates the flow at any point on a link as a function of the density at that same point. This is usually combined with a traffic conservation equation which requires that traffic does not enter or leave except at the end of the link (Carey and McCartney, 2004).

The "cell transmission model" (CTM) (Daganzo, 1995) is a popular traffic performance model. It spatially discretizes links into homogeneous cells of equal length and traffic flow is evaluated at every cell. The model defines a set of rules by which the inflow to each cell is controlled. Inflow to a cell is the minimum of three values: the existing vehicles on the upstream cell, the inflow capacity of the cell, and the remaining capacity of the cell (Sumalee et al., 2011).

The "link transmission model" (LTM) (Yperman 2007) determines the link travel times given a time-varying traffic demand and the split proportions at each junction. The network consists of links l(i;j) and the evolution of traffic on the road network is represented by the cumulative number of vehicles that pass the nodes i and j by time t. The method involves a traffic flow model and a node model. First, for each link at each time interval, the traffic flow model determines the sending flow at the downstream end i.e. the maximum number of vehicles that can be sent to following links in case of an unlimited out flow, and the receiving flow at the upstream end i.e. the maximum number of vehicles that can be received by the link in case of an infinite traffic demand. Then, the node model determines which parts of these sending and receiving flows can actually be sent and received according to the split proportions. Accordingly, vehicles are transferred from upstream (sending) to downstream (receiving) links and the cumulative vehicle numbers at the boundaries of the connected links are updated.

2.4 Equilibrium

It is common in urban transportation planning to assume that traffic flows in an urban network approach equilibrium (i.e. where the traffic load is evenly scattered over the routes). Recently however, there has been an emerging stream of research questioning the validity of the equilibrium theory in the context of traffic assignment. The case against the assumption of equilibrium is based on two arguments. Firstly, it is claimed that there is not yet empirical proof that traffic flows conform to the rules and constraints imposed by the equilibrium theory (Tampere et al., 2010). Furthermore, and especially in the evacuation situation, observation of traffic flows show network flows are different from what any equilibrium formulation would predict (Prater et al., 2000, Dow and Cutter, 2002). The second argument questions the validity of the assumptions on which equilibrium concepts are based such as a traveler's awareness of network conditions and consistent rational choice. Accordingly, two non-equilibrium DTA approaches are proposed in the literature. First, Dynamic Process models, also known as Doubly Dynamic models, view equilibrium as an attractor, i.e. a state that the system, over time, evolves towards it but may only achieve under certain conditions. Temporal evolution in this model is modeled by the Markov Chain process which relates the current state of the system to its previous state. Watling and Hazelton (2003) give an extensive review of dynamic process models. The second approach applies game-theoretical techniques such as competitive and cooperative games to DTA and is capable of accommodating different equilibrium points for different classes of road users in one network (Yang et al., 2008).

Despite all the arguments, equilibrium assignment still remains common practice and its formulations include user optimal, system optimal, boundedly rational user optimal, stochastic user optimal, deluded, and fuzzy user equilibrium. User equilibrium (UE) is the state of the network in which travel cost for every traveler is minimum and no individual can improve their situation (i.e. decrease their costs) by unilaterally changing their route. System optimal equilibrium is the state in which the travel cost throughout the whole system is minimum (but not necessarily for each traveler). Boundedly rational user optimal is achieved when all users are satisfied with their current travel choice. In this framework, every traveler has an "indifference band", defined as a range of acceptable travel cost such that a traveler would not switch from their current route if the perceived travel cost is within that band (Mahmassani and Chang, 1987). Stochastic user optimal equilibrium is the state of the network in which the "perceived" travel cost of every traveler (as represented by a probabilistic expression of travel cost) is minimized and cannot be improved by unilaterally changing routes. In deluded equilibrium, travelers are locked in delusions (such as not being aware of all alternatives or fully knowing some of them) and do not believe their perceived travel times can be improved by changing routes (Nakayama et al., 1999). Fuzzy user equilibrium is an extended UE for dynamic systems into near-equilibrium state and describes the situation in which travel costs are described in fuzzy terms resulting in each used route between an O-D pair having approximately the same cost and it is almost minimal (Ridwan, 2003).

2.5 DTA Approaches

DTA approaches are usually distinguished based on being analytical or simulation-based. Analytical models consist of optimizing an objective function subject to a set of constraints which collectively describe the feasible area of the solutions to a problem. Analytical models applied to route choice consist of three parts: route choice criteria (reflected in the objective function), flow conservation, and flow propagation models within individual routes (both reflected in constraints). Simulation-based DTA models basically follow the same problem formulation as analytical models but while solving the problem, address the constraints of the assignment through simulation. Thus, simulation refers to a solution methodology rather than a formulation of the problem (Peeta and Ziliaskopoulos, 2001). Analytical and simulation-based approaches are somewhat different in the network loading models they apply. While whole link model are used in analytical methods, queuing, divided travel time, and the wave model have been used in simulation based methods and cell transmission models are employed in both approaches.

2.5.1 Analytical Models

Analytical DTA models can be divided into equilibrium and non-equilibrium models. Non-equilibrium models were discussed earlier. Equilibrium-based analytical models can be categorized based on their demand elasticity assumption (elastic vs. inelastic demand), time representation (continuous vs. discrete time), variable level (link level, route level, combination of both), and model formulation. Based on model formulation, analytical methods can be divided into three groups, namely: mathematical programming, optimal control, and variational inequality models. The specifications of each group are discussed in the following sections.

2.5.1.1 Mathematical Programming Formulations

In mathematical programming formulations of equilibrium-based traffic assignment, the objective function typically pursues achievement of traffic equilibrium within the network.

For instance, in pursuing user equilibrium, the objective function would be to minimize the expression in Equation (2.5) where x^n_l and t^n_l are the traffic volume and the travel time on link l during time interval n, respectively, and T is the time horizon of the analysis.

$$\sum_{n=1}^{T}\sum_{l}\int_{0}^{x_l^n} t_l^n(u)du \tag{2.5}$$

A concern in mathematical programming is that preserving the convexity of constraints requires compromise on traffic realism. For instance, using well-calibrated link impedance functions, explicitly addressing the first-in first-out (FIFO) property through constraints or any use of integer variables, removes the convexity or linearity of the model and this can result in loss of tractability of the model. Merchant and Nemhauser (1978), as the seminal work in the field of dynamic traffic assignment, developed a discrete-time, non-linear, non-convex mathematical programming model (henceforth referred to as the M-N model) which provided a temporal generalization of static system optimal assignment.

Non-convexity of the M-N model originated from inclusion of the FIFO equality in the constraint set. Carey (1987) and Nie (2010) proposed traffic performance functions that would transform this equality to an inequality which conformed to the convexity requirement. Another approach to address the non-convexity issue was to avoid addressing FIFO by explicit constraints, for instance, by adopting CTM performance models (Ziliaskopoulos, 2000) or the expanded time-space network concept (Carey and Subrahmanian, 2000).

The issue of non-linearity in mathematical programming has often been addressed by using the bi-level programming approach. In this approach, the objective function is formulated as a summation of two terms, one representing the user or system optimal minimization and the other representing the departure time optimization. The whole optimization problem is then decomposed into two subproblems, each of which optimizes one term of the main objective function subject to a subset of linear convex constraints. Subproblems are then solved iteratively. Janson (1991), Jayakrishnan et al. (1995) and Nie (2010) have used this approach in their formulations.

2.5.1.2 Optimal Control Formulations

Optimal Control Theory (OCT) is applied in systems in which a stack level (state variable) can be adjusted by input and/or output levels (control variables). An optimal control problem consists of optimizing an objective function of time, control, and state variables by determining the temporal evolution of the control variable subject to a set of constraints.

By adopting the traffic volume of a route (link) as the state variable and route inflow as the control variable, Friesz et al. (1989) formulated DTA as an optimal control problem. While link inflows are usually taken as control variables, Boyce et al. (1995) used both link inflow and exit flows as control variables and Lam and Huang (1995) adopted the splitting rates of traffic flows at nodes as the control variables.

OCT has been used in formulation of reactive user and system optimal equilibrium assignments. It has also been used in assignment problems including departure time choice in which an additional state variable needs to be added to the route (link) volume such as the cumulative number of vehicles departing from an origin towards a destination through a route within a time interval (Boyce et al., 1995).

2.5.1.3 Variational Inequality Formulations

A remarkable advantage of the variational inequality (VI) method over mathematical programming is that VI does not require the Jacobian[1] of the cost matrix to be symmetrical, and hence yields a more realistic formulation of the assignment problem.

Equation (2.6) demonstrates a route-based dynamic user equilibrium assignment formulated as a VI problem.

$$\int_{o}^{T} \sum_{rs} \sum_{a} \eta_p^{rs^*}(t)\left[f_p^{rs}(t) - f_p^{rs^*}(t)\right]dt \geq 0 \qquad (2.6)$$

[1] The Jacobian in this case is the matrix of first-order partial derivatives of the route flows with respect to the route costs.

where T is the time horizon of the analysis, the decision variable, $f^{rs}{}_{p}(t)$, is the traffic flow from origin r to destination s at time t, $\eta^{rs}{}_{p}(t)$ is the cost of traveling from origin r to destination s through route p at time t, a is the set of the links of the network, and the asterisk denotes the optimal solution. The feasible region for path flows is delineated by the same constraints used in mathematical programming.

One of the main features distinguishing different VI DTA models is the solution algorithm adopted. These include the projection method (Jang et al., 2005), relaxation method (Shin and Lee, 2002), and nested diagonalization method (Chen and Hsueh, 1997).

2.5.2 Simulation-based Models

Simulation models can be divided into three groups based on their level of detail. Microscopic models simulate individual vehicles while macroscopic models aggregate traffic flow and mesoscopic models function in between. Microscopic models demand extensive data and computing capability but provide more detailed outputs and more realistic representations of network flow while macroscopic models are relatively moderate in their input and processing requirements and in their output level of detail.

Various simulation software programs have been developed specifically for evacuation applications such as EVAQ (Pel et al., 2008), ETDFS (PBS&J 2000), OREMS (Rathi and Solanki, 1993), NETVAC (She et al., 1982), NETSIM (KLD,), DYNEV (KLD, 1984), and CLEAR (McLean et al., 1983). General traffic simulation software has also been applied to evacuation problems of which examples are PARAMICS used by Cova and Johnson (2003), VISSIM used by Han and Yuan (2005), INTEGRATION used by Mitchell and Radwan (2006), CORSIM used by Williams et al. (2007), DynaMIT used by Balakrishna et al. (2008), DynusT used by Noh et al. (2009), and TransCAD used by Wang et al. (2010).

2.6 Route Choice Criteria

Wardrop (1952) first proposed minimizing travel time as the criterion for route choice and for several decades travel time was the most important and often the sole criterion considered in modeling travelers' route choice. The late eighties and early nineties witnessed the emergence of new route choice criteria. Pursula and Talvitie (1992) employed the concept of generalized costs which was a combination of travel time and travel monetary costs. Adler et al. (1993) extended the single measure travel impedance to utility functions which were expressed in terms of several criteria for alternative routes. Bonsall and Parry (1990) and Khattak et al. (1991) indicated that for every-day trips in familiar areas, travelers prefer to choose their usual (habitual) route instead of selecting the route with the maximum utility. Yang et al. (1993) found driver's experiences to be of significance in route selection. Many studies, including Uchida et al. (1994), concluded that traffic information and driver's perception of such information are important criteria affecting the route choice. Doherty and Miller (2000) found travelers residential and employment location, economic status and stage in life, coordinating schedules with other household members and acquaintance with the route to be influential in the choice process outcome. Golledge and Gärling (2001) added exposure to truck or heavy freight traffic, deviation from the straight line shortcut between the origin and destination, and the likelihood of being patrolled by enforcement authorities to the list. Papinski et al. (2009) and Chen et al. (2001) added the following list to the route choice criteria: late and early arrival penalties, congestion, travel time reliability (travel time variance or the probability that the actual travel time deviates from the perceived value), travel distance, number of turns, number of stop lights and stop signs, scenery and aesthetics, travel comfort, travel safety, curvilinearity of the road, number of roads, and facility class.

Evacuation route choice has been modeled using criteria other than travel time. Dow and Cutter (2002) observed a significant bias toward using interstates during an evacuation. Chiu and Mirchandani (2008) found familiarity with the route to be of importance in evacuation route choice. Pel et al. (2008) employed route travel time and overlap factors as route choice variables. Overlap factors measured the similarity between the evacuee's departure time, route and destination with what had been instructed by officials.

2.7 Concluding Remarks

To the best of the author's knowledge, despite all the efforts which have led to remarkable discoveries about evacuee traffic behavior, a definitive set of variables determining the route choice behavior during evacuation from a hurricane has yet to be explored. Moreover, the dynamics of the model parameters deserve more focus. This suggests clarification on the dynamics of model parameter change with the approach of a storm.

Chapter 3 Data Description and Preparation

3.1. Data Description

Data used for model calibration came from a study aimed at developing a new data collection methodology of hurricane evacuation behavior (Gudishala and Wilmot, 2010). The study collected revealed and stated choice evacuation behavior by administering a mail-out mail-back self-administered survey for revealed preference data, and an animation of alternatives for the stated choice survey. The survey collected data from 300 households in New Orleans and surrounding parishes. The revealed preference portion of the study collected actual evacuation behavior from hurricane Gustav, along with the households' socio-economic data. In the stated choice portion of the survey each household was shown three hypothetical storms audio-visually and they were asked to state their behavioral intentions.

A total of nine hypothetical storms were used to elicit stated behavior from the sampled households. In the stated choice survey, households were presented with conditions surrounding a hypothetical hurricane and asked at various stages during its approach to report whether they would evacuate or not. If a household said they would evacuate then they were asked to provide details of their evacuation such as their intended mode of travel, time of evacuation, type of refuge sought, location of the refuge, and the route they would use to reach their destination. For every hypothetical storm, four time-dependent scenarios were presented to the respondent and on each they were asked to report their expected behavior. In each scenario, information was provided on the time of day, day of the week, storm category, type of evacuation order in effect (i.e. none, recommended, or mandatory), the projected path of the storm, and the expected time left to landfall. For example, in storm 1, scenario 1, the following information was provided verbally and written on the screen: "The time is 10:15 am Wednesday and a category 4 storm is approaching through a given path (illustrated in the DVD) and is expected to make landfall in 70 hours. No evacuation order has been issued." The projected path of the hurricane was shown on the screen. The respondent was then asked if their household would evacuate at this time or not. If they chose to evacuate, further information on the evacuation was requested, and the respondent was then directed to the next storm. If the household chose not to evacuate, this was recorded and the respondent was routed to scenario 2 of storm 1. In scenario 2 the following information was provided to the respondent: "The time is now 6:15 am on Thursday, the storm is still a category 4 and the expected time to landfall is 50 hours and a voluntary evacuation has been issued." The path of the hurricane up to that point and its predicted path in the future were shown on the screen, and the respondent was asked whether their household would evacuate or not. The process was repeated until the respondent either stated they would evacuate or they proceeded through all four timed scenarios of a particular storm without evacuating, and were then directed to the next storm.

When respondents indicated they would evacuate, they were asked to state the route they would choose to reach their destination. In the data collected, routes selected by respondents were I-10, I-55, I-59, US 61, US 90, US 190, and the Lake Pontchartrain Causeway. Obviously, for each destination, only routes which connected the New Orleans area to the destination city were considered available. For example, for respondents who selected Mobile in Alabama as their destination, I-10 and US90 were the only available routes.

3.2. Data Preparation

Some processing was required to adjust the data into the format required to calibrate the route choice model. This mainly involved data cleaning, grouping the observations, and time standardization. Grouping was carried out to transform data into fewer destinations to provide enough observations for calibrating the model. Time standardization involved aggregating data collected from different scenarios into common time frames. The following subsections explain these processes in detail.

In cleaning the data base, a major issue was dealing with inconsistent entries. For example, some respondents had mentioned a route which did not lead them to their stated destination. These entries were mainly removed since it was not possible to impute the correct entry. Another issue was the inconsistencies between the city names and the states which respondents had mentioned their destination to be located in. Considering the fact that occasionally there are several cities with same name located in different states, there was the matter of distinguishing between errors and similar destination names.

3.2.1. Grouping the Observations

Respondents selected a wide variety of destinations for their evacuation. The list of stated destinations included approximately 100 cities with less than ten journeys statedly made to most of them. The large number of destinations would have made model calibration difficult and the small sample in many of the destinations would have compromised the model's accuracy. To address this issue, two remedies were adopted. The first was to bundle destinations into geographically proximate groups to get more observations on journeys heading towards a generally common destination. Grouping was carried out subject to access being by the same segments of the same routes i.e. cities in a group had to be reachable from the New Orleans area by all members of that group's route choice set. This criterion also resulted in members of each group being geographically close to each other. Groups were mutually exclusive and collectively exhaustive.

As an example, twenty four journeys were statedly made to Baton Rouge which were grouped with two journeys headed for Zachary, three for Addis, two for Prairieville, and three for St. Francisville to make group number 6 with thirty four journeys. Members of this group are shown in Figure 3.1. Cities in group 6 could be reached with any of the members of the choice set of this group which was: {I-10, US61, I-55 + I-12}. Table 3.1 demonstrates cities bundled in each group and number of journeys statedly made to them. Figure 3.2 shows the location and approximate boundaries of groups 6, 8, and 13 to give examples of grouping.

3.2.2. Temporal Standardization of Observations

In the data set, each storm had a time frame different from the others. For example, in storm number 1, the time in the first scenario is presented as Wednesday 10:15 AM with landfall of the hurricane expected 70 hours later on Saturday at 8:15 AM. In storm number

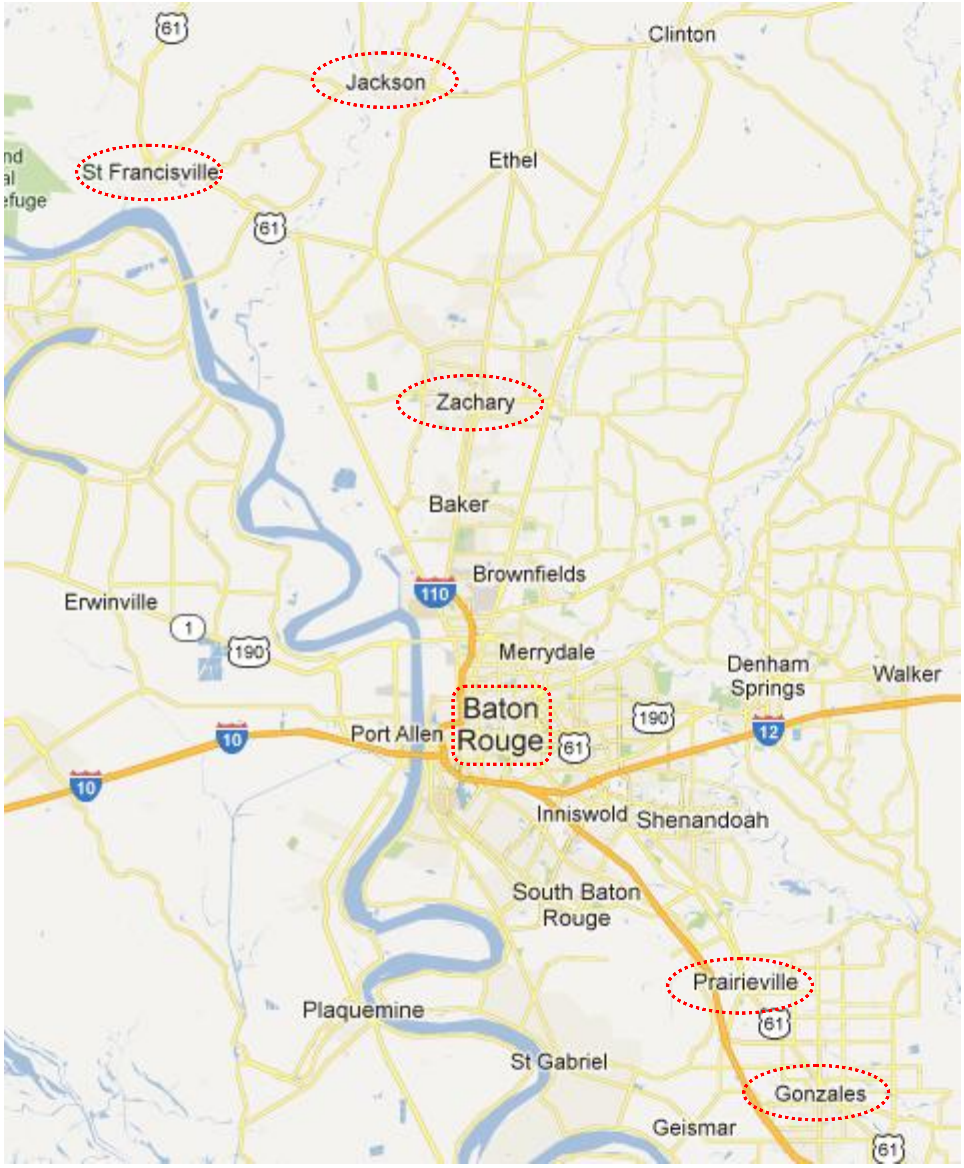

Figure 3.1 Cities of group 6

2, the time in the first scenario is Monday 12:30 p.m. with storm landfall expected on Thursday at 12:30 p.m. Now suppose respondent A answered questions on storm number 1 and respondent B answered questions on storm number 2 and both respondents stated that they would evacuate on Wednesday at 9:00 p.m. For storm number 1, this time would be 57.75 hours before landfall and for storm number 2 this time would be 15.5 hours before landfall. Hence, although the actual times of evacuation of the respondents 1 and 2 are the same, the conditions under which they are making their route choice are different in terms of time to hurricane landfall. Time to landfall affects route choice because it affects urgency, and the significance and accuracy of the projected path of the storm and its impact on individual routes. Other temporal aspects of the evacuation situation such as storm intensity or time of day do not affect route choice although they do affect other aspects of evacuation such as whether to evacuate and when to do so.

To make data on different storms compatible, a reference point related to time to landfall was defined for all storms and the stated evacuation times were set according to this reference point. For each storm, 192 hours (=8×24) before the time of landfall was set as the reference point. For example, as shown in Figure 3.3, respondent A who evacuated 57.75 hours prior to landfall, synonymously evacuated 134.25 hours after time recording was initiated at the reference point. Respondent B is also shown on the time axis at 15.5 hours before landfall and 176.5 hours from the reference point.

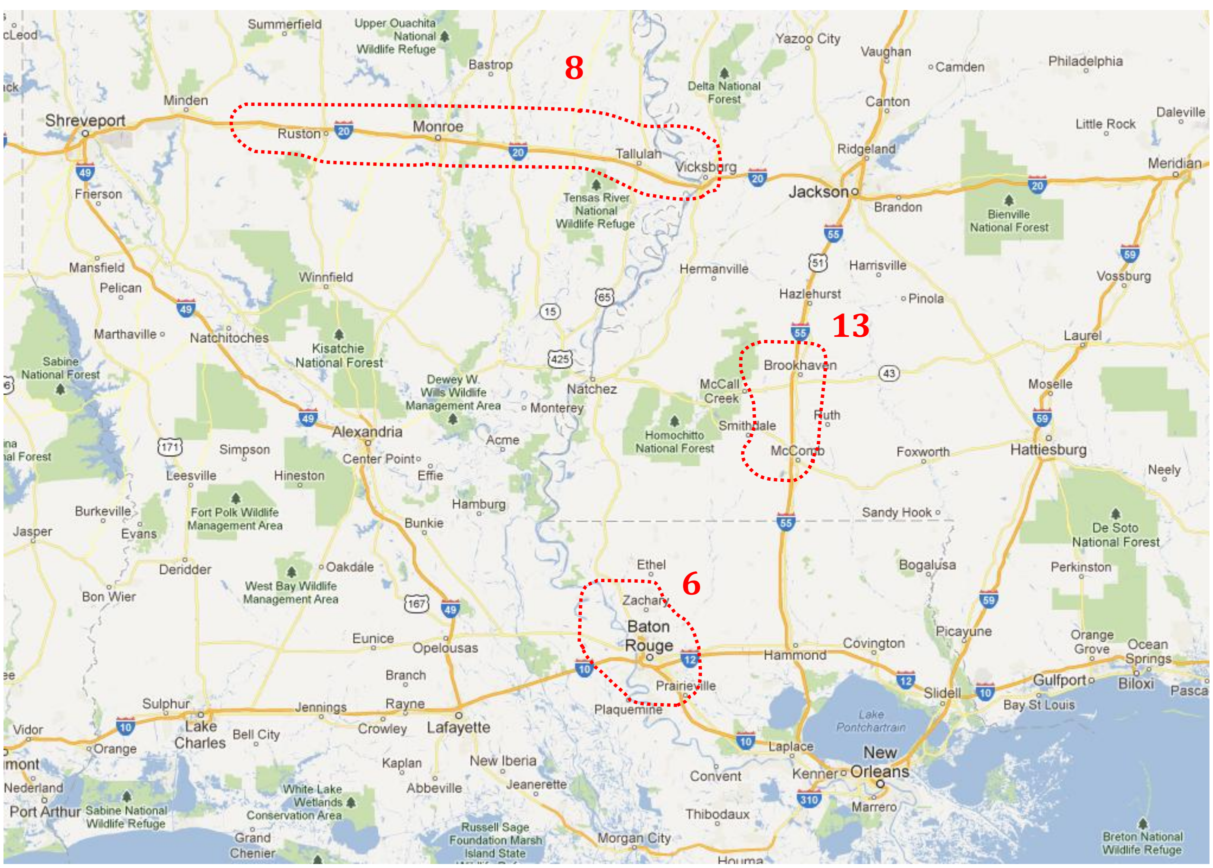

Figure 3.2 Location and boundaries of groups 6, 8, 13

Table 3.1 Groups of destination cities

Group	City	Number of Journeys
1	Atlanta (LA), Montgomery, Natchez(LA), Natchitoches, Georgetown, Jena	25
2	Covington, Abita Springs	7
3	McComb, Brookhaven, Natchez (MS), Tylertown	13
4	Memphis, Tunica, Grenada (MS), Batesville, Houston (MS), Cookstation, Austin (MS), Clarksdale, Killen (AL), Oxford (MS), Pontotoc (MS), Jackson, Madison (MS), Yazoo City (MS), Richland, Canton, Cary, Orlando (OK), Pinola	61
5	Bunkie, Mansura, Marksville, Meridian (LA)	9
6	Baton Rouge, Zachary, Gonzales, Jackson, Addis, St. Francisville, Prairieville	34
7	Independence (LA), Amite, Hammond	10
8	Monroe, West Monroe, Madison (LA), Ruston, Vicksburg	16
9	Atlanta (GA), Covington (GA), Sparta (NC)	25
11	Houston (TX), Missouri City, San Antonio, Albuquerque, Lake Charles, Phoenix (AR), Forest (TX), Las Vegas, Spurger(TX)	48
12	Nashville, Houston (TN), Brentwood, Murfreesboro	12
13	Destin, Pensacola, Panama City, Orange Beach (AL), Gonzalez (FL), Laurel (FL), Tallahassee	28
14	Mobile (TN), Fairhope, Little Creek	11
15	Birmingham, Gadsden, Gatlinburg, Huntsville, Arlington (AL)	10
16	Little Rock, Arkadelphia, Hot Springs	10
17	Shreveport, Fair Play (TX), De Queen (AR)	16
18	Dallas	13
	TOTAL	348

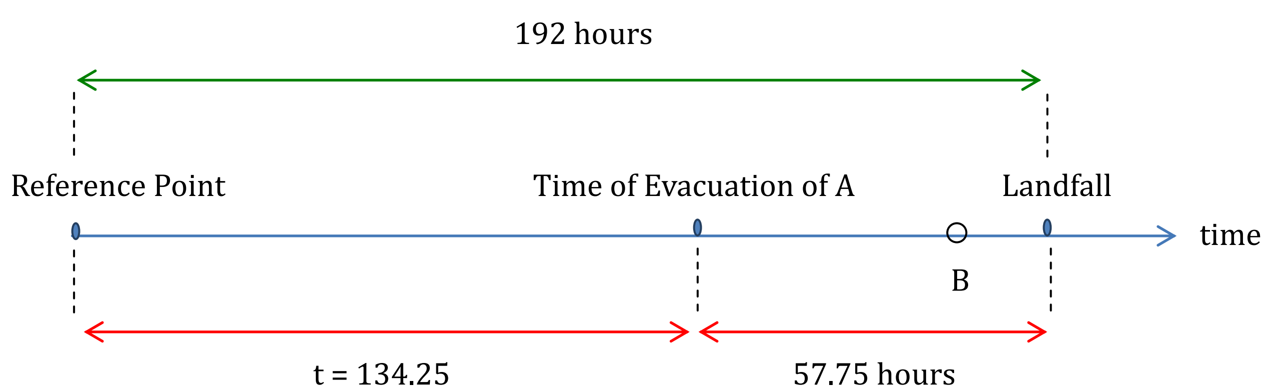

Figure 3.3 An example of time standardization

By performing this standardization of "time of evacuation" for all stated evacuations, a data base consisting of 348 lines, one for each stated evacuation shown in Table 3.1, was established. A sample data base is shown in Table 3.2 with each line of data set showing the household identification number, time of evacuation, destination, selected route, and attributes of the chosen route. These route attributes are explained in the next section.

Table 3.2 A sample of the data set

HOUSEHOLD ID	EVACUATION TIME	DESTINATION	ROUTE	ACCESSIBILITY	SAFETY	FACILITY CLASS	DISTANCE	SERVICE	FAMILIARITY	PSERVICE
6340	26	1	1	36.54	54.62	0	255	0.18	51235.2	9222.3
9620	98	3	4	38.25	86.5	0	285	0.12	21736.5	2608.4
5866	21	6	3	1.33	91.04	1	144	0.15	13284.7	1992.7
5747	151.75	7	5	7.26	74.5	1	62	0.23	14000	3220

This data set was used to calibrate the route choice model by applying the method explained in chapter 4. The temporal distribution of evacuations is shown in Figure 3.4 where data are aggregated into six-hour time intervals from the reference point of 192 hours before hurricane landfall. The graph shows relatively low numbers of stated evacuations at the leftmost and rightmost parts of the horizontal axis, since this is when a storm is either very distant or very close, respectively. The median of the evacuations is at 111.5 and mode at 96.5 hours from the reference point. Having a mean equal to 107.75 suggests that the distribution is skewed to the left.

Figure 3.5 shows the cumulative departure curve of evacuees after time standardization. This curve is similar to an S-shaped curve and shows that the temporal standardization of observations is approximately reproducing the evacuation trip production curve.

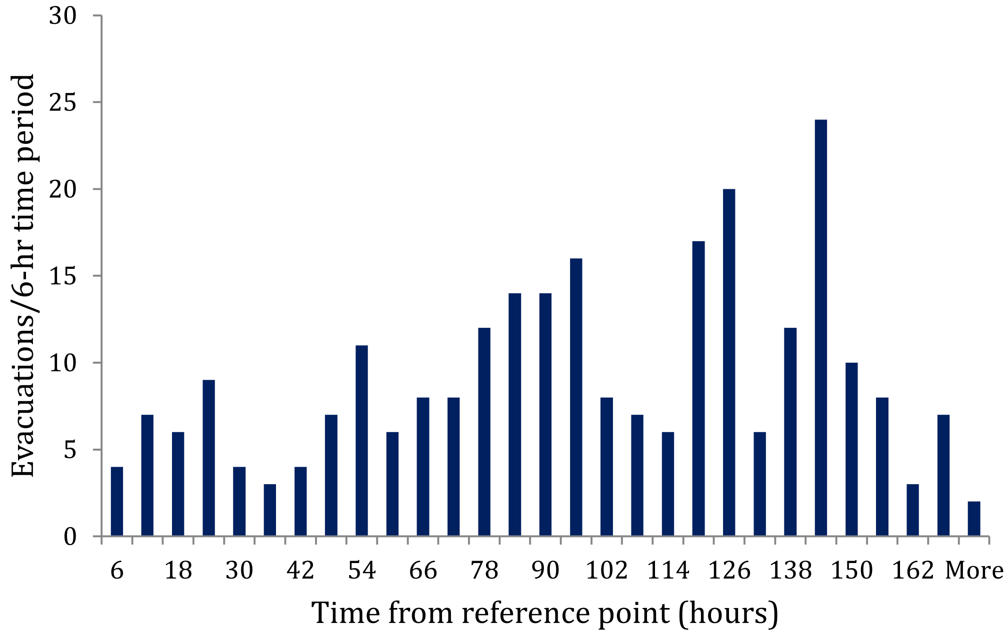

Figure 3.4 Stated evacuation frequencies per six-hour time interval

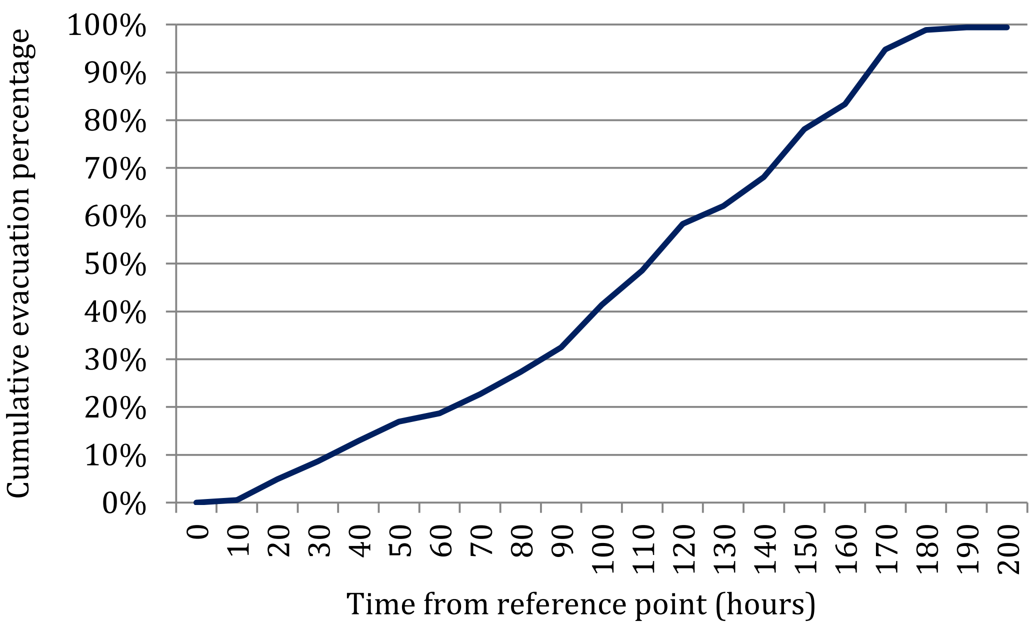

Figure 3.5 Cumulative departures of evacuees after time standardization

3.2.3. Calculation of Variables

Based on the discussion presented in section 1.2.1 and also from experience, literature, and availability of data, six variables were selected as candidate variables in the model. These were: familiarity, accessibility, service accessibility, facility class, safety, and distance. The following sections define each of these variables and explain how they were calculated using available data.

3.2.3.1. Familiarity

Intuitively, the more a route is used, the more drivers are familiar with it. Thus, the number of vehicles that use a specific route in normal (i.e. non-extreme) conditions, for all trip purposes, was used as an expression of familiarity. To achieve this, traffic values were normalized to yield the familiarity factor (FF) shown in Equation 3.1. In the equation, the familiarity factor for route p is a function of l_{ip} and x_{ip} where l_{ip} is the length of link i on route p and x_{ip} is the typical number of vehicles on link i during non-evacuation conditions. C is the set of all alternative routes between a specific origin/destination pair. Higher values of FF_p indicate higher familiarity. For a specific origin/destination pair, the sum of FF_p over all alternative routes is 1.

$$FF_p = \frac{\sum_{i=1}^{n_p} l_{ip} x_{ip}}{\sum_{p \in C} \sum_{i=1}^{n_p} l_{ip} x_{ip}} \tag{3.1}$$

Since the sense of familiarity is achieved by drivers regardless of their trip purpose, it was important to include all trip purposes in the traffic volume calculation. For this reason, weekday off-peak volumes and also weekend volumes needed to be included in the traffic volume data. Considering this, the Average Annual Daily Traffic (AADT) was a suitable expression of average travel on a facility and was the measure of traffic (x_{ip}) used on each road segment. Data on AADT was obtained from the Louisiana Department of Transportation and Development (LA DOTD) (http://www.dotd.la.gov/). This data base consists of information on AADT for six years (1997, 1998, 2001, 2004, 2007, 2010) but only the three most recent years were used to better represent the current level of familiarity with these routes. The data base also includes the mile point and longitude and latitude of the measurement location so the traffic on each section of the road can be identified.

The average AADT at each measurement station was calculated using the three most recent year's observations of traffic volumes and then the distance which this volume relates to was calculated (l_{ip}). As shown in Figure 3.5 and Equation 3.2, for each measurement station, this distance is half way from the previous measurement station and half way to the next measurement station. d(i; j) is the distance between count stations i and j. Average AADT was multiplied by this distance and summed over all road segments in a route.

$$l_{ip} = \frac{d(i-1,i)}{2} + \frac{d(i,i+1)}{2} \tag{3.2}$$

Intuitively, acquaintance with parts of routes that are far away from the residence of a household would not have a significant effect on the familiarity variable. Therefore, only parts of routes that were located within the borders of the state of Louisiana were included in the calculation of familiarity.

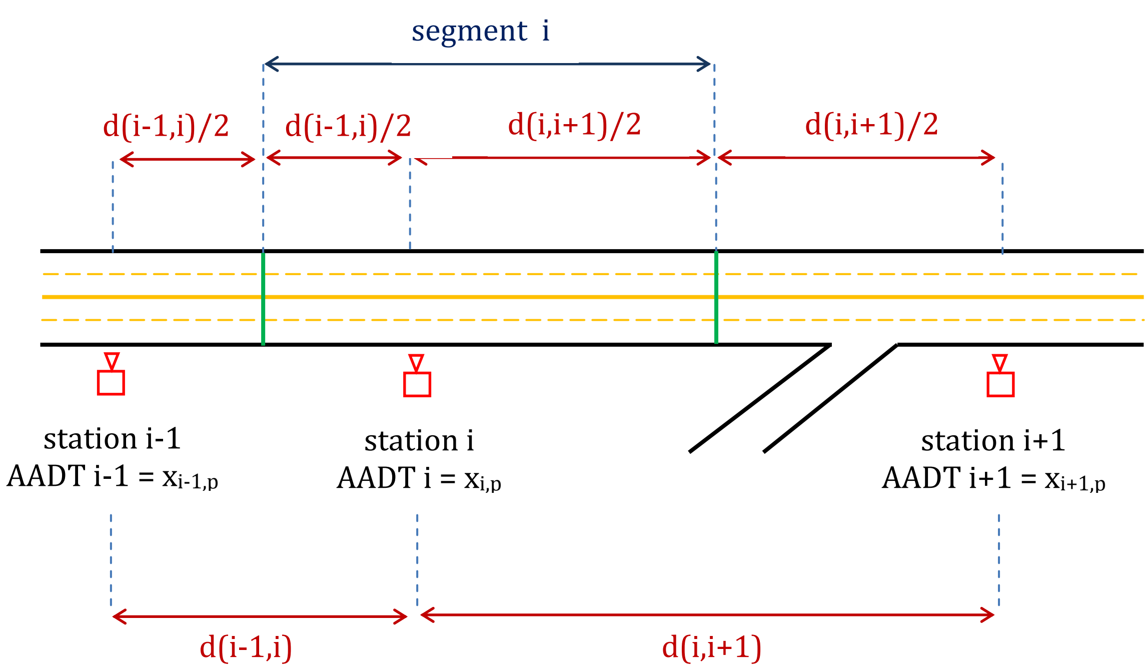

Figure 3.5 Segmentation of roads based on the location of measurement points

3.2.3.2. Accessibility

Accessibility of a route for a household was defined as the shortest aerial distance between the household's residence and the route. Geographical location of household residences had been recorded in the data base and the minimum distance between these locations and the representative points of each route were calculated using TransCad and Microsoft Excel.

Figure 3.6 shows an example of accessibility calculated for a household residence located in New Orleans at the intersection of Cleveland Avenue and St. Telemachus Street. The red circle shows the location of the residence and the green arrows show the closest airline distance to the respective routes. These values are used as measures of accessibility.

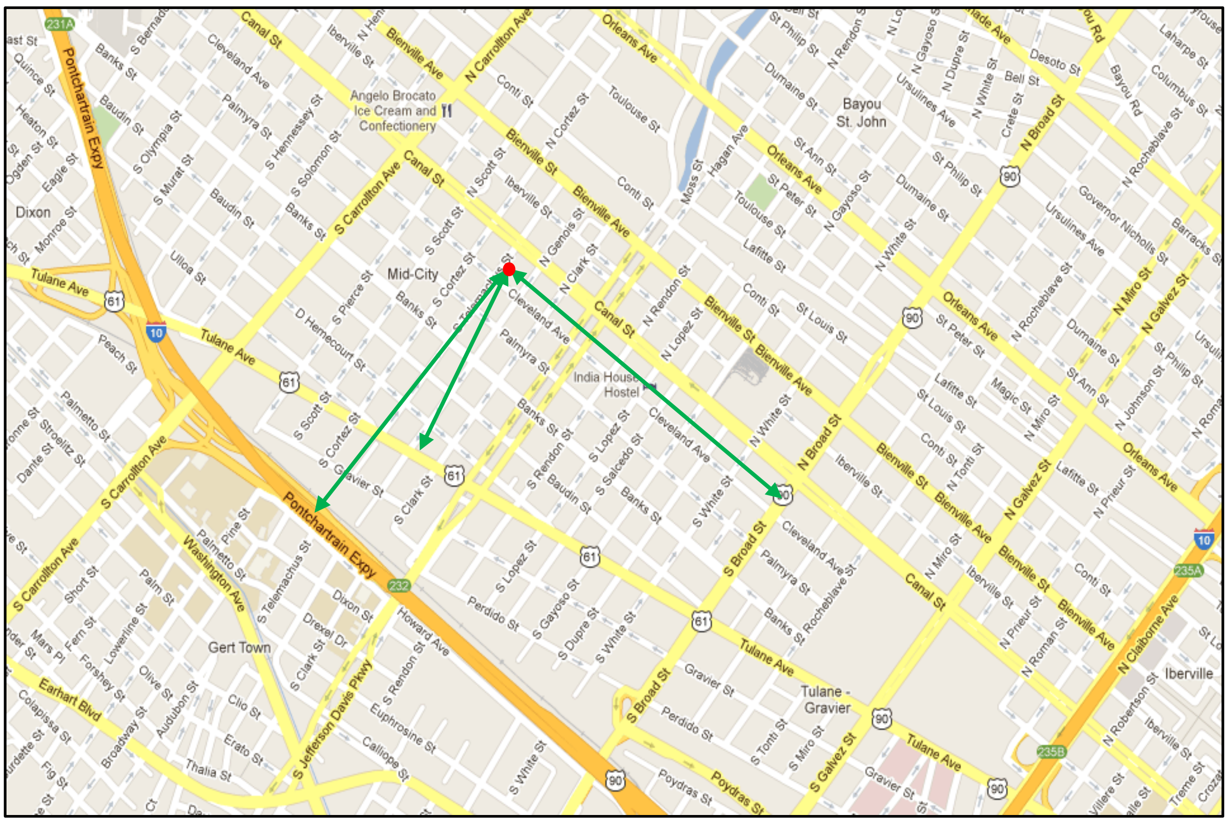

Figure 3.6 an example of accessibility calculated from I-10, US-61, and US-90

By considering the spatial distribution of the respondents shown in Figure 3.7, the importance of accessibility in evacuation route choice becomes more apparent. For example respondents who live in St. Tammany parish and plan to evacuate to Baton Rouge are far from I-10 and US-61 but relatively close to I-12. This disutility which intuitively affects the route choice of the respondent is not reflected in other variables of the model. Respondents that are not too far from some of the alternative routes may also prefer the closer ones. This hypothesis is tested and discussed in the fifth chapter.

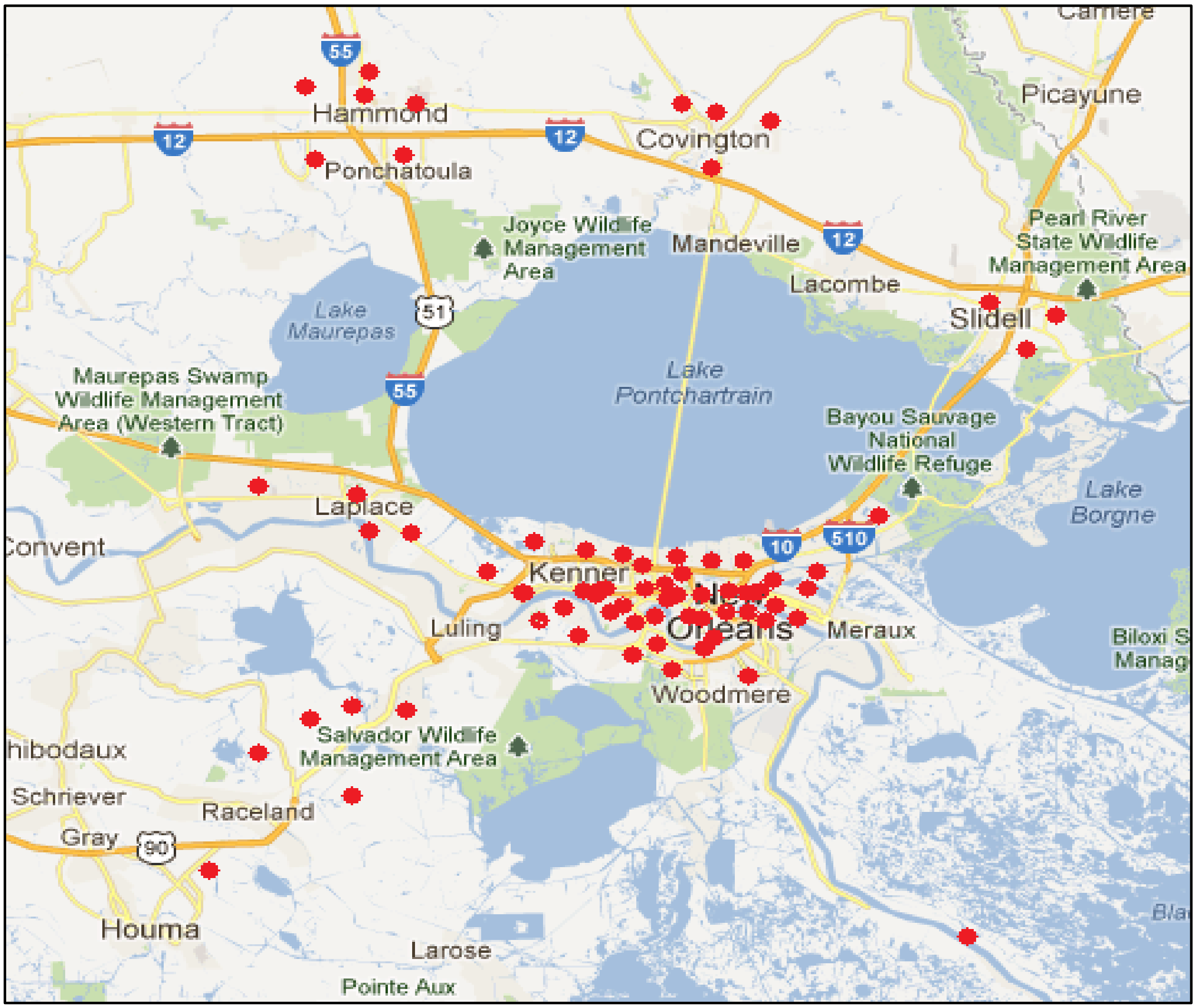

Figure 3.7 Spatial distribution of respondents

3.2.3.3. Distance

Intuitively evacuees prefer to reach their destinations as soon as possible. Therefore shorter routes are expected to be more appealing. When seeking the shortest path, length of a route could be stated in terms of its travel time or distance. To have an estimate of the travel time of a route one needs to know the level of congestion on the route. In stated choice data bases like the data used for this research, respondents are not in the actual condition of evacuation and hence do not have a perception of the level of congestion on each route. On the other hand, respondents can be assumed to have a perception of distance and consider it in their stated route choice preference. Therefore, distance was used in this research.

The distance (length) of each route connecting New Orleans to selected destinations was calculated using Google Map's distance measurement tool. For destinations on the north or west side of New Orleans, distance was measured as the length of each route from the junction of I-10 and I-310 to the center of the destination group. For US-61 and US-90 a point close to this point was selected for distance measurement. For destinations located in east and northeast of New Orleans, distance between the junction of I-10 and I-59, and the destination group was measured.

For groups that included a city considerably larger than other members of the group, the big city was considered as the center. For groups including cities of similar population and area, approximate geographical center was considered for measuring the distance. For example in group 1, Atlanta (LA) and in group 4, Memphis were considered as the centers of their groups, respectively.

3.2.3.4. Service

The number of gas stations and hotels on each route was used to represent the service availability of that route. These data were obtained from Google Map by observing facilities that were close enough to be seen from the road as these were the only ones that were assumed to have an effect on an evacuee's perception of the availability of services. The total number of gas stations and hotels was then divided by the length of the route to yield a "per mile" measure of service availability on the route. For longer routes which connected New Orleans to distant destinations such as Atlanta and Houston, only the first hundred miles of the routes where considered in calculation of service. The reason for this was that route choice within the first 100 miles was more likely to be subject to congestion and unpredictable delay than later portions of the route and therefore weigh more heavily in route choice.

3.2.3.5. Facility Class

A dummy variable was used to indicate whether the route is an interstate or not. Zero was assigned to interstate highways (I-10, I-55, I-12, and I-59) and one was assigned to other roads (US-61, US-90, and US-190). This variable was used to determine whether there was an innate preference for freeways for evacuation as suggested in the literature review.

3.2.3.6. Perceived Service

On the premise that existing service stations (and places of accommodation) on a route will not influence route choice if evacuees are unaware of them, a variable combining familiarity and service availability was introduced. This variable was called "perceived service" and was calculated by multiplying familiarity and service. The variable measures the exposure of services to the public. The intention was to consider using this variable in place of "service" and "familiarity" and not in addition to them.

3.2.3.7. Safety

Safety measures the risk of storm conditions being experienced on a route. It was considered as a dynamic variable in that the risk would vary depending on the predicted path of the storm at any point in time. The closest distance between the predicted path of a hurricane and a route was used as the safety level of the route at that time. Where available, the measurement stations used in calculating the familiarity factor were used as representative points on each route. Latitude and longitude of the measurement stations were obtained from the same source as the AADTs. For other routes, several points were located using Google Map. The path of the center of each storm was obtained from the data base and latitude and longitudes were calculated using TransCad. Then the minimum distance between the path of the storm and each route was calculated and used as an indicator of the route's safety.

The predicted paths of storm presented to respondents at each of four stages of a scenario were the predicted paths as obtained from official predictions of that storm from the National Hurricane Center. This is shown in Figure 3.8 where the red, navy and purple curves show the predicted path of a storm presented to respondents of a scenario at stages 1, 2, and 3 respectively. The predicted path of the storm at stage 4 is assumed to be identical to that at stage 3. It is also assumed that the route being analyzed is that part of I55 that connects New Orleans to Jackson. The difference between these predicted hurricane paths would affect the calculation of safety factor because those who had decided to evacuate earlier had seen a different storm path than those who had decided to evacuate later. To address this issue, the time of evacuation of respondents was used to find out which storm path they had responded to, and the safety variable was then calculated for that specific path. For instance, in Figure 3.8 if a respondent had stated they would evacuate at a time which was between t_2 and t_3 then they would have considered the navy curve as the path of the storm and d_2 would be the minimum distance between the path of the storm and alternative route 3 which would be the value of safety variable for this alternative. On the other hand, if the stated evacuation time of a respondent that had been presented by the same storm was greater than t_3, then the purple curve would have been the path considered by the respondent and since the storm path intersects the route, the minimum distance between storm path and alternative route 3 would be zero which would be the value of the safety variable for this alternative.

The underlying assumption of this calculation is that respondents would not answer the evacuation question with "yes" and then state the time of their evacuation much later than the time presented to them. In other words, those respondents who said they would evacuate between t_i and t_{i+1} are responding to situation at stage i and not earlier stages.

3.2.4. Time Interval Definition

The whole analysis period needed to be divided into shorter time intervals so that route choice behavior of evacuees at each time interval could be modeled and compared with other times. Based on the temporal distribution of data, analysis time was divided into two time intervals. The first time interval starts from 192 hours and ends at 110 hours prior to

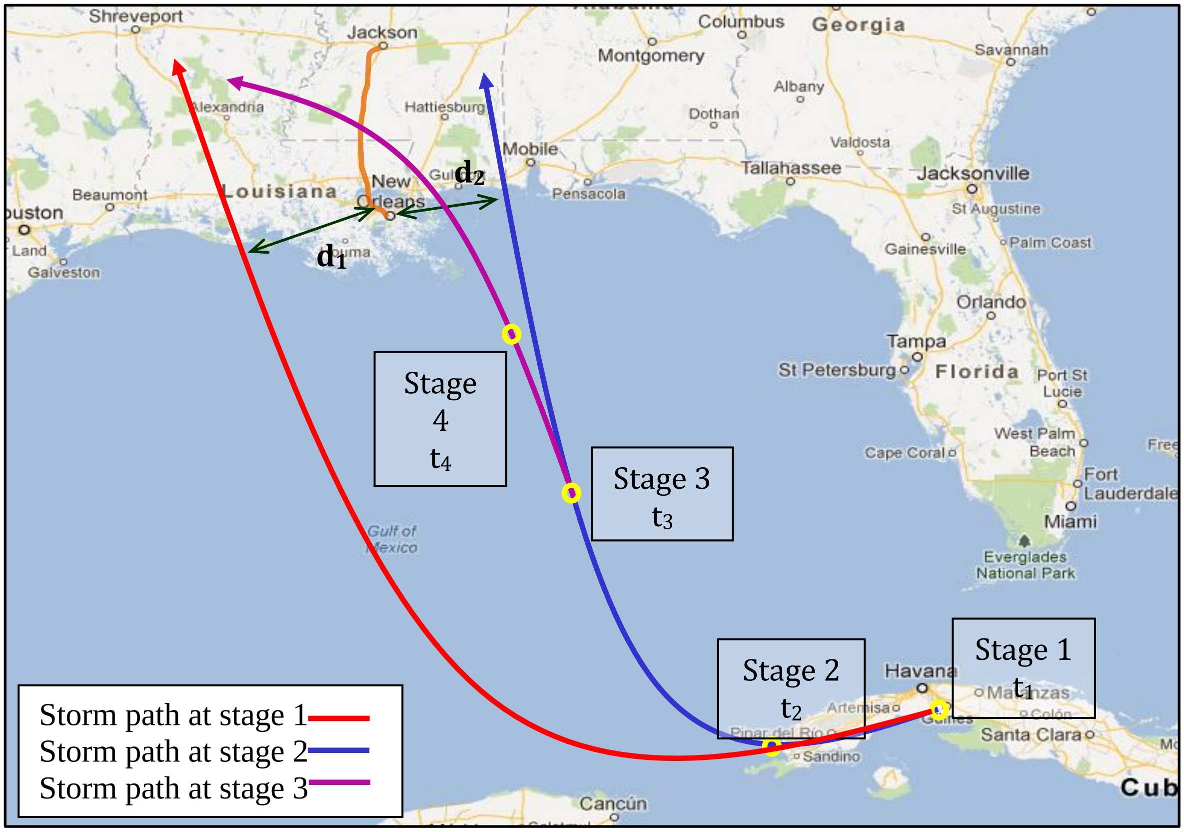

Figure 3.8 Calculation of safety in different stages

landfall (i.e. 0 hours to 82 hours from the reference point in Figure 3.3). The second time interval starts at 110 hours and ends at landfall. This setting for time intervals was selected to provide sufficient observations in each time interval for calibration of the route choice model. Length of the first time interval is 82 hours and the length of the second time interval is 110 hours. 169 journeys took place in first time interval (henceforth called risk averse evacuees) and 179 in the second (henceforth called risk tolerant evacuees).

3.3. Validation Data

Recorded traffic volumes on routes going outbound from New Orleans collected at the time of Hurricane Katrina was used for validation of the model. Data were obtained from New Orleans Regional Commission as reported by Wolshon and McArdle (2009) and included the traffic volumes on dates August 28 and 29, 2005 which is shortly before the landfall of

Hurricane Katrina. Traffic volumes were 96,388 on I-10 westbound close to Baton Rouge, 73,550 on I-12 westbound and close to Baton Rouge, and 33,612 on US-61 westbound. Model outputs for the same points were derived and then the observed values and predicted values were compared and plotted to see how well the model reproduces the real situation. Due to the low number of available validation data points, no statistical tests of the comparative values were run.

Chapter 4 Methodology

In this chapter model specifications are first explained. Then in section 4.2 the theoretical background of the model is given and details of calculations are explained. Then, methods adopted for model calibration, hypotheses testing, and model validation are discussed.

4.1. Model Specification

Specifications of the model including its underlying assumptions, functional form, and variable specifications are explained in the following subsections.

4.1.1. Model Assumptions

According to characteristics of the data set and the process of data collection, it was assumed that respondents were independent entities i.e. choices made by one household did not affect the choice made by others. It was also assumed that the decision process followed by respondents was rational i.e. respondents consistently maximized their utility when selecting their route. Moreover, alternative routes were assumed to be independent. Independence of alternatives along with independence and rationality of respondents lay at the foundation of the choice model used in this. The route choice process was assumed to be utility-based.

The whole evacuation period was divided into two time intervals (as described in section 3.2.4) and a route choice model was calibrated for each. It was assumed that the taste which respondents display in making route choice stays the same within each time interval. Moreover, it was assumed that the route choice made at the outset of the trip is maintained throughout and not altered in response to conditions on the network while the evacuation trip in the progress. Thus, the model developed in this research is a pre-trip route choice model.

It is also assumed that the decision for evacuation (trip generation) and selection of evacuation destination (trip distribution) are carried out prior to the route choice step described in this research and this step does not have any feedback effect on prior steps.

4.1.2. Functional Form

According to the nature of route choice, a discrete choice model was required in this research. Based on the assumptions in 4.1.1 and convenience, the logit functional form was considered as appropriate choice of type of discrete choice model. Details on how to derive a logit function is explained in section (4.2.1). Except for a small segment (less than 10 miles) of I-10 and I12+I55 which connect New Orleans to Baton Rouge, all alternative routes were distinct (without any common segments) so ordinary logit was considered appropriate for this research.

4.1.3. Variable Specification

As discussed in chapter 3, model input or the criteria assumed to affect the route choice of respondents are: familiarity, service availability, perceived service, accessibility, safety, distance, and functional class. All these variables except for accessibility are attributes of alternatives. Accessibility is an attribute of both the route and the individual (household). The dependent variable of the model is the probability of selecting a route. By knowing the demand matrix, these probabilities can be transformed to traffic volumes on each route as shown in section 4.2.2.

4.2. Theoretical Background

In the following sections, a brief overview of logit models is given to provide the context for the model used in this study.

4.2.1. Overview of Logit Models

In models based on the concept of utility, as shown in Equation 4.1 below, it is assumed that an alternative is selected if its utility is higher than the utility of any other alternative. Therefore, the probability of selecting an alternative is equal to the probability of its utility being higher than all others. In random utility models – of which logit is one - it is assumed that a utility function (U_j) consists of a systematic term (V_j) and a random term (ε_j). The systematic part of the utility function is represented by the attributes of alternatives or of the individual (or household). The random term on the other hand accounts for, as stated earlier, the impact of unobserved attributes, unobserved taste variations, measurement error, imperfect information, and the use of proxy variables on observed choice. Equation 4.2 shows the structure of a typical linear utility function. Substituting Equation 4.2 into 4.1 yields Equations 4.3 and 4.4 where x_{jr} is one of R variables included in the utility function, β's are parameters of the model and P_j denotes the probability of selecting alternative j.

$$P_j = \text{Prob}\left\{U_j \geq U_i\right\}, \ \forall\, i \neq j \tag{4.1}$$

$$U_j = \sum_{r=1}^{R} \beta_r x_{jr} + \varepsilon_j = V_j + \varepsilon_j \tag{4.2}$$

$$P_j = \text{Prob}\left\{V_j + \varepsilon_j \geq V_i + \varepsilon_i\right\}, \ \forall\, i \neq j \tag{4.3}$$

$$P_j = \text{Prob}\left\{\varepsilon_i - \varepsilon_j \leq V_i + V_j \ \right\}, \ \forall\, i \neq j \tag{4.4}$$

To analytically calculate the probability in Equation 4.4, one needs to know the distribution of ε but this distribution cannot be determined due to the origin and nature of the effects entering the random term. Instead, plausible assumptions are made on the distribution of ε. By assuming that the random terms are independently and identically Gumbel (also known as type I extreme value) distributed, the logit model is derived as the analytical expression solving Equation 4.4 (Ben Akiva and Lerman, 1985). A typical logit function is shown in Equation 4.5 where **x** is the vector of variables considered by the model to be affecting the choice and **β** is the vector of parameters of the model; m is the number of alternatives.

$$P_j = \frac{e^{\boldsymbol{\beta}'\mathbf{x}_j}}{\sum_i^m e^{\boldsymbol{\beta}'\mathbf{x}_i}} \tag{4.5}$$

Using the logit model to determine evacuation route choice, the formulation of the model would normally take the form shown in Equation 4.6. P_{jdt} is the probability of selecting route j at time t in order to evacuate from New Orleans to destination group d. m_d is the number of routes connecting New Orleans to destination group d. $\mathbf{x}_{idt}$ is the vector of the variables pertaining to route i connecting New Orleans to destination group d at time t. $\boldsymbol{\beta}_t$ is the vector of parameters of the model at time t. With this model, and assuming independence among alternate routes and households, a model can be estimated for each combination of destination d and time t provided sufficient observations exist for each combination. However, this is not the case in this study since the number of observations to individual destination groups ranges between 7 and 61 for all time periods combined as shown in Table 3.1. On the other hand, if it is assumed that routes are fully described by their attributes then destinations and time are not significant and all observations can be grouped together to estimate a single route choice model as shown in Equation 4.7. According to Ortúzar (2001) and Ben Akiva (1977), the choice set need not be identical for individuals in a logit model. In fact, every individual may have a specific choice set to select from. In the current case, respondents evacuating to a particular destination group will have the same route choice set, but those evacuating to other destination groups will have a different choice set. All choices in the universal choice set are included in at least several choice sets in the sample.

$$P_{jdt} = \frac{e^{\boldsymbol{\beta}_t' \mathbf{x}_{jdt}}}{\sum_i^{m_d} e^{\boldsymbol{\beta}_t' \mathbf{x}_{idt}}} \tag{4.6}$$

$$P_j = \frac{e^{\boldsymbol{\beta} \cdot \mathbf{x}_{jdt}}}{\sum_i^{m_d} e^{\boldsymbol{\beta} \cdot \mathbf{x}_{idt}}} \quad \forall d, t \tag{4.7}$$

4.2.2. Traffic Volume Calculation

To transform model outputs of probabilities to traffic volumes, an origin-destination (O-D) demand matrix is required; something which is standard input to trip assignment. By multiplying the total demand for a destination group by the probability of selecting each route, traffic volume of that route is calculated. In the following calculations, it is assumed that these O-D matrices are known, and they are known by time period. That is, K_{dt} is the demand for evacuation to destination group d in time interval t. Then, if v_{jdt} is the traffic volume in time interval t on route j which connects New Orleans to destination group d, it can be estimated from the following expression:

$$v_{jdt} = K_{dt} \times P_{jt} \tag{4.8}$$

It should be noted that the time t referred to in Equation 4.8 is the time period in which the demand is reported. Typically, this is usually in terms of 2-hour or 6-hour time periods, thus providing time-dependent route flows which, in turn, can be input to network loading models to estimate travel time, density, delay, and queue lengths on links within individual routes. This network loading activity of the entire dynamic traffic assignment process was not conducted as part of this research effort.

4.3. Model Calibration

Calibrating a model is basically estimating parameters of the model such that the model comes as close as possible to reproducing revealed or stated data. Estimating parameters includes determining their means and variances. Logit models are calibrated using the method of maximum likelihood. In the maximum likelihood method a likelihood function is first defined and then maximized with respect to model parameters. As shown in Equation 4.9, the expression of likelihood is the joint probability of all observations under the assumption that the probabilities of successive choices are independent of each other. $P_n(j)$ is the probability that respondent n chooses route j and y_{jn} is a binary function which attains the value of 1 if respondent n chose route j and is zero otherwise.

$$L = \prod_{n=1}^{N} \prod_{j=1}^{M} P_n(j)^{y_{jn}} \tag{4.9}$$

As the log function is a strictly monotonically increasing function, L and its log are maximized by the same values of β. On the other hand, working with a function in additive form is more convenient than one in multiplicative form. Therefore, in the maximization process L is replaced with its logarithm ln(L) as shown in Equation 4.10.

$$\ln(L) = \sum_{n=1}^{N} \sum_{j=1}^{M} y_{jn} \ln P_n(j) \tag{4.10}$$

Values of parameters that maximize the log likelihood function must satisfy the first and second order conditions shown in Equations 4.11 and 4.12.

$$\frac{\partial \ln(L)}{\partial \boldsymbol{\beta}} = \sum_{n=1}^{N} \sum_{j=1}^{M} y_{jn} \left[\mathbf{x}_{ij} - \sum_{j=1}^{M} P_n(j) \mathbf{x}_{ij} \right] = 0 \tag{4.11}$$

$$\frac{\partial^2 \ln(L)}{\partial \boldsymbol{\beta}\, \partial \boldsymbol{\beta}'} = - \sum_{n=1}^{N} \sum_{j=1}^{M} P_n(j) \left[\mathbf{x}_{ij} - \sum_{j=1}^{M} P_n(j) \mathbf{x}_{ij} \right] . \left[\mathbf{x}_{ij} - \sum_{j=1}^{M} P_n(j) \mathbf{x}_{ij} \right]' < 0 \tag{4.12}$$

The covariance matrix ($\boldsymbol{\Sigma}$) of estimated parameters is estimated from the matrix shown in Equation 4.13 where $\hat{\beta}$ denotes the estimated parameters.

$$\Sigma = \left(\frac{\partial^2 \ln L(\hat{\boldsymbol{\beta}})}{\partial \hat{\boldsymbol{\beta}}\, \partial \hat{\boldsymbol{\beta}}'} \right)^{-1} \tag{4.13}$$

Using the described method, a vector of model parameters ($\boldsymbol{\beta}$) was estimated. This vector of parameter values together with values of variables pertaining to each route for each household was input to Equation 4.7 to estimate the probability of selecting alternative route j. The covariance matrix ($\boldsymbol{\Sigma}$) permits statistical tests to be conducted on the parameters.

4.3.1. Measuring Goodness-Of-Fit

Goodness-of-fit, as the name suggests, measures how well a calibrated model reproduces the behavior recorded in the data on which it was estimated. Among the first features of the estimated model to be examined at calibration are the sign, relative value, and significance of the estimated parameters. Coefficients with the wrong sign or unexpected value may indicate biased estimation. The statistical insignificance of coefficients of variables that are expected to have an effect on choice may indicate strong correlation among variables.

The likelihood ratio index (ρ^2) is a common measure of goodness-of-fit of discrete choice models. This index is similar to R^2 in regression analysis in that its value also varies between zero and one to depict a non-existent to perfect fit, respectively. However, its magnitude must be interpreted differently in that it does not explain the proportion of variation in the data explained by the model as in R^2. Rather, ρ^2 values of 0.3 or 0.4 indicate a good fit to the data.

Equation 4.14 shows the definition of the likelihood ratio index. $L(\hat{\boldsymbol{\beta}})$ is the value of the log likelihood with estimated parameters and $L(\mathbf{0})$ is the value of the log likelihood function when all parameters are set equal to zero.

$$\rho^2 = 1 - \frac{L(\hat{\boldsymbol{\beta}})}{L(\mathbf{0})} \tag{4.14}$$

4.3.2. Hypothesis Tests

In this study, hypothesis tests are conducted on models estimated on all observations and then separately on observations from the two time intervals defined in 3.2.4. Within the same time interval, the asymptotic t test is used to examine whether individual parameters of the model differ from a specific constant. Equation 4.14 shows the null hypothesis and the statistic used for testing if β_k is equal to a constant number c. The hat sign denotes the estimated value and $\widehat{var}(\beta_k)$ is the estimated variance of β_k.

$$H_0: \beta_k = c \tag{4.15}$$

$$t = \frac{\widehat{\beta_k} - c}{\sqrt{\widehat{var}(\beta_k)}} \tag{4.16}$$

Statistic t shown in Equation 4.16 follows a Student t distribution with degrees of freedom equal to the number of observations minus one. Following selection of a tolerable type I error, the critical value (t_c) is derived from tables and if t is greater than t_c, the null hypothesis is rejected. Within the same time interval, the t-test is used to determine whether individual model parameter values are significantly different to zero (i.e. c = 0). This determines whether the variable associated with each parameter makes a significant contribution to the value of the dependent variable or not.

Hypothesis testing among the two time intervals includes a test in which the parameters of a model estimated in one time interval has the same parameter values, collectively, as a model estimated in the other time interval. That is, the null and alternative hypotheses are:

$$H_0: \boldsymbol{\beta}_1 = \boldsymbol{\beta}_2 \tag{4.17}$$
$$H_A: \boldsymbol{\beta}_1 \neq \boldsymbol{\beta}_2$$

In the context of this research, rejection of the null hypothesis indicates that evacuation route choice behavior is different among households evacuating in the two time periods, that is risk tolerant and risk averse evacuees.

The test statistic for this test is shown in Equation 4.18. To estimate the statistic, a pooled model is first estimated using data from all time intervals and the likelihood value for the pooled model (L_{pooled}) is recorded. Then data are divided by time interval and models estimated on data from each time interval. The likelihood values of time intervals (L_t) are then recorded for each time interval t.

$$X = 2(L_{pooled} - \sum_{t=1}^{T} L_t) \tag{4.18}$$

Statistic X follows a Chi-square distribution with degrees of freedom equal to the number of variables of the model. T is the number of time intervals in the analysis period which is equal to 2 in this research.

4.3.3. Elasticity in the Model

Elasticity (E) is the percentage change in the dependent variable resulting from one percent change in one of the independent variables. In the context of this research, as shown in Equation 4.19 elasticity represents the responsiveness of the probability of selecting a route to a change in the value of some attribute of the route. Moreover, in the current context, elasticity can be defined in three different ways. Firstly, the percentage change in the probability of selecting route k resulting from one percent change in an attribute of route k (direct elasticity). Secondly, the percentage change in probability of selecting route k resulting from one percent change in an attribute of route j which connects New Orleans to the same destination group (cross elasticity). Thirdly, the percentage change in the probability of selecting route k resulting from one percent change in an attribute of route q which connects New Orleans to a different destination group. The third elasticity is equal to zero because it is assumed that determining the destination is done before the route choice. Therefore, routes connecting New Orleans to different route groups are not being compared by respondents. Equations 4.19 and 4.20 show the direct and cross elasticities of the model. x_{rk} is attribute r of route k.

$$E_{x_r}^{P_k} = \frac{\frac{\partial P_k}{\partial x_r}}{\frac{P_k}{x_r}} = \frac{\partial P_k}{\partial x_r} \times \frac{x_r}{P_k} = \frac{\partial \left(\frac{e^{\boldsymbol{\beta}' \mathbf{x}_k}}{\sum_{j=1}^{m_d} e^{\boldsymbol{\beta}' \mathbf{x}_j}} \right)}{\partial x_r} \times \frac{x_r}{\left(\frac{e^{\boldsymbol{\beta}' \mathbf{x}_k}}{\sum_{j=1}^{m_d} e^{\boldsymbol{\beta}' \mathbf{x}_j}} \right)} \tag{4.19}$$

$$\therefore E_{x_{rk}}^{P_k} = (1 - P_k)\beta_r x_{rk} \tag{4.20}$$

$$\therefore E_{x_{rj}}^{P_k} = -P_j \beta_r x_{rj} \tag{4.21}$$

Equation 4.19 shows that greater the probability of selecting a route, the less it is affected with changes in attributes of the route.

Chapter 5 Results and Conclusions

5.1. Results

Route choice models were calibrated using the procedure explained in chapters 3 and 4. Models were estimated on all observations combined, and then separately on observations of households which evacuated either before or after 110 hours before hurricane landfall. Disregarding the time interval for which the model was estimated, Equation 5.1 shows the model formulation. The left hand side of the equation shows the probability of selecting route j connecting New Orleans to destination group d, β_r denotes the parameter of the model for variable r in time interval t. x_{rjd} denote variable r of alternative route j to destination t. R is the number of variables included in the model and m_d is the number of routes connecting New Orleans to destination group d. The model has a common specification for all destinations.

$$P_{jd} = \frac{e^{\sum_{r=1}^{R} \beta_r x_{rjd}}}{\sum_{j=1}^{m_d} e^{\boldsymbol{\beta}' \mathbf{x}_j}} \quad \forall d \tag{5.1}$$

Variables included in the model are accessibility, facility class, distance, safety, service, familiarity, and perceived service. Perceived service is defined as the product of service and familiarity. In the following sections, route 1 refers to I-10, route 2 is {I55+I12}, and route 3 is US61 which connect New Orleans to Baton Rouge. Other routes to other destinations are similarly numbered. Figure 5.1 shows these routes. Route 1 is colored blue, route 2 is colored red and route 3 is colored green.

5.1.1. Correlation among the Variables

As the first step in determining the combination of variables to include in the model, correlations should be measured. Highly correlated variables should not be included in the model since correlation among variables inflates the estimated variance of the coefficients of correlated variables.

The correlation matrix in Table (5.1) shows that except for familiarity and service, there is no other high correlation among variables. High correlation between service and familiarity may be due to more traffic attracting more business. This high correlation suggests that service and familiarity should not be used in the model together. Therefore instead of service and familiarity, perceived service as described in 3.2.3.6 was used in the modeling.

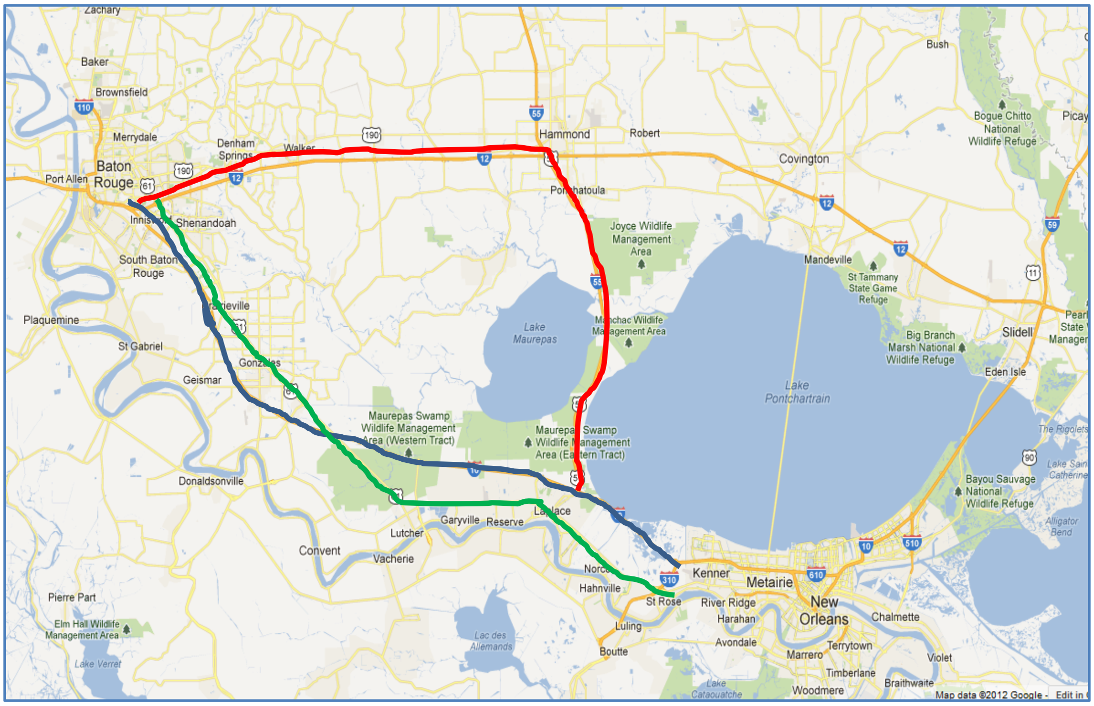

Figure 5.1 Routes connecting New Orleans to Baton Rouge

Table 5.1 Correlation among variables in the pooled data

	Accessibility	Distance	Facility class	Service	Pservice	Familiarity	Safety
Accessibility	1.00	0.06	0.00	-0.29	0.02	-0.29	-0.05
Distance		1.00	-0.09	0.00	0.09	-0.02	0.11
Facility class			1.00	-0.06	-0.59	-0.04	-0.06
Service				1.00	0.18	0.98	0.05
PService					1.00	0.14	0.02
Familiarity						1.00	0.06
Safety							1.00

5.1.1. Models with One Variable

As the second step, the effects of variables on route choice were examined one by one to measure the impact each attribute has on the route choice in the absence of others. Table 5.2 shows the results. Columns under T1 and T2 show results for the first and second time intervals, respectively. Columns under "pooled" show results of the model with all observations without time discrimination. The p denotes the p-value (the probability of obtaining a test statistic at least as extreme as the one that was actually observed, assuming that the null hypothesis is true) and L denotes the value of the log likelihood at convergence. "Access" stands for accessibility and "Fam" stands for familiarity.

Table 5.2 Results of models with one variable

	T1 (risk averse)			T2 (risk tolerant)			POOLED		
VAR	β	p	L	β	p	L	β	p	L
Access.	-0.03	0.00	-178.8	-0.04	0.00	-189.2	-0.04	0.00	-368.0
Distance	-0.01	0.00	-179.7	-0.01	0.00	-189.4	-0.01	0.00	-369.1
Facility	-1.39	0.00	-169.8	-1.67	0.00	-174.1	-1.53	0.00	-344.2
Service	1×10^{-5}	0.33	-187.6	5×10^{-5}	0.01	-194.9	3×10^{-5}	0.01	-383.2
PService	16×10^{-5}	0.00	-173.9	2×10^{-4}	0.00	-176.2	1×10^{-4}	0.00	-350.6
Fam.	3×10^{-6}	0.15	-186.4	1×10^{-5}	0.01	-195.3	5×10^{-6}	0.00	-382.5

As can be seen in Table 5.1, accessibility, distance, perceived service and facility class are statistically significant in both T1 and T2. Familiarity and service are not significant in T1 but are significant in T2. On the other hand, their product (Pservice) is highly significant in both time intervals. As one would expect, values of parameters in the pooled model are usually between values of T1 and T2. The best (least absolute value) value of the log likelihood under T1 (i.e. when the storm is distant) is -169.8 achieved by running the model on facility class alone in first time interval. For T2 the best value of the log likelihood is -174.1 by facility class (same variable as T1).

Table 5.4 also suggests that in the first time interval, neither familiarity nor service are not significant yet their product (perceived service) is. Thus, while it was determined not to use them together in the model, it also seems that they are not useful individually anyway.

5.1.2. Models with Multiple Variables

Based on the results of the one-variable models, several combinations of significant variables were tested to find the combination which yields the best model i.e. the model with the lowest log likelihood value. This model was called "the final model". Among the tested models, two are reported and discussed in the following sections and the rest are reported in the Appendix.

5.1.2.1. The Final Model

The model including accessibility, distance, facility class, and perceived service yielded the best overall results. The estimation results of this model are shown in Table 5.5.

Table 5.5 Estimation results of the final hurricane evacuation model

	T1 (risk averse)		T2 (risk tolerant)		POOLED	
VARIABLE	β	p- value	β	p- value	β	p- value
Accessibility	-0.04	0.00	-0.05	0.00	-0.044	0.01
Distance	-0.01	0.00	-0.01	0.00	-0.01	0.06
Facility Class	-0.96	0.00	-0.99	0.00	-0.97	0.03
PService	1×10^{-4}	0.00	2×10^{-4}	0.00	1.3×10^{-4}	0.02
LL(β)	-150.6		-146.8		-298.4	
LL(0)	-187.4		-199.7		-387.2	
ρ^2	0.2		0.27		0.23	
observations	169		179		348	

All variables are statistically significant in both time intervals. The coefficient of distance is negative which is logical in that the longer a route is, the less likely it will be selected. Interstate highways are expected to be more attractive for evacuation than other highways which suggests a negative sign for the coefficient of facility class as 0 denoted freeway and 1 denoted other types of roads. On the other hand, perceived service (pservice in the table), which is the product of familiarity and service is expected to have a positive effect on the probability of selecting a route because both greater familiarity and more service will attract evacuees to that route and boost its share relative to those of other routes. Accessibility which shows the distance between a route and the residence of a household has a negative sign which suggests that evacuees prefer routes that are passing closer to them and are probably more accessible to them.

By running the likelihood test mentioned earlier in chapter 4, $2(L_{pooled} - L_1 - L_2)$ was equal to 1 which does not exceed the X_c^2 with value of 9.49. Therefore, we found that the model parameters for time intervals 1 and 2 are not significantly different from each other. This shows that based on the data at hand, generally, the evaluation of evacuation route choices does not change as a storm approaches.

5.1.2.2. Another Useful Model

The final model reported in previous section does not include the safety variable. The reason for excluding safety was that adding it made facility class insignificant. In this model, similar to the final model, the vector of parameters fail to reject the null hypothesis ($\boldsymbol{\beta}_1=\boldsymbol{\beta}_2$) mentioned in Equation 4.29. This implies that models with safety do not distinguish between risk averse and risk tolerant evacuees either. Results of the model including safety are reported in Table 5.6.

Table 5.6 Results of the model including the safety factor

	T1 (risk averse)		T2 (risk tolerant)		POOLED	
VARIABLE	β	P- value	β	P- value	β	P- value
Accessibility	-0.05	0.00	-0.05	0.00	-0.05	0.00
Distance	-0.009	0.00	-0.007	0.03	-0.008	0.00
Facility Class	-0.45	0.18	-0.50	0.18	-0.47	0.06
PService	1.7×10^{-4}	0.00	2.2×10^{-4}	0.00	2×10^{-4}	0.00
Safety	0.04	0.00	0.04	0.01	0.04	0.00
LL(β)	-145.3		-143		-289	
LL(0)	-187.4		-199.7		-387.2	
ρ^2	0.22		0.28		0.25	
observations	169		179		348	

5.1.3. Model Validation

Validation data would only permit for validating the T2 model as collected data belonged to two days prior to landfall. From traffic counts for two days prior to the landfall of

Hurricane Katrina traffic volumes on routes connecting New Orleans to Baton Rouge were 72066 on I-10 (route 1), 33669 on I55+I12 (route 2), and 43572 on US-61 (route 3). Synonymously, the traffic volume ratio of I-10 over I55+I12 is 2.14 and the odds ratio of I-10 over US-61 is 1.65. Equations (5.2) through (5.11) below show the values of the variables input to the model estimated in Table 5.5 to produce model estimates of the odds ratios. Vector x is the vector of model variables and x1, x2, and x3 denote values of variables for I-10, I55+I12, and US-61 respectively. Perceived service is calculated by multiplying values of service and familiarity for each route. The value for accessibility is replaced by its average and cancels out throughout the calculations.

$$\mathbf{x} = (\text{accessibility, distance, facility class, pservice}) \tag{5.3}$$

$$\mathbf{x_1} = (14.6, 60, 0, 0.16\times 51225.7) \tag{5.4}$$

$$\mathbf{x_2} = (14.6, 75, 0, 0.1\times 36845.8) \tag{5.5}$$

$$\mathbf{x_3} = (14.6, 60, 1, 0.34\times 23817.6) \tag{5.6}$$

$$\boldsymbol{\beta} = (-0.05, -0.01, -0.99, 0.0002) \tag{5.7}$$

$$P_1 = \frac{e^{\sum_{r=1}^{R}\beta_r x_{rjd}}}{\sum_{j=1}^{m_d} e^{\boldsymbol{\beta}'\mathbf{x}_j}} = 0.567 \tag{5.8}$$

$$P_2 = \frac{e^{\sum_{r=1}^{R}\beta_r x_{rjd}}}{\sum_{j=1}^{m_d} e^{\boldsymbol{\beta}'\mathbf{x}_j}} = 0.225 \tag{5.9}$$

$$P_3 = \frac{e^{\sum_{r=1}^{R}\beta_r x_{rjd}}}{\sum_{j=1}^{m_d} e^{\boldsymbol{\beta}'\mathbf{x}_j}} = 0.208 \tag{5.10}$$

Replacing values of probabilities in Equations 4.8 and having K equal to the sum of volumes on three alternative routes (72066+33669+43572=149307), predicted values of traffic volumes would be 84665, 33628, and 31014 for routes 1, 2, and 3 respectively. Figure 5.1 shows the predicted and observed traffic volumes plotted.

These predicted values showed 17.5, 0.1, and 28 percent error for routes 1, 2, and 3 respectively. The order of volumes were predicted correctly i.e. route 1 had the largest traffic volume, then route 3 and then route 2.

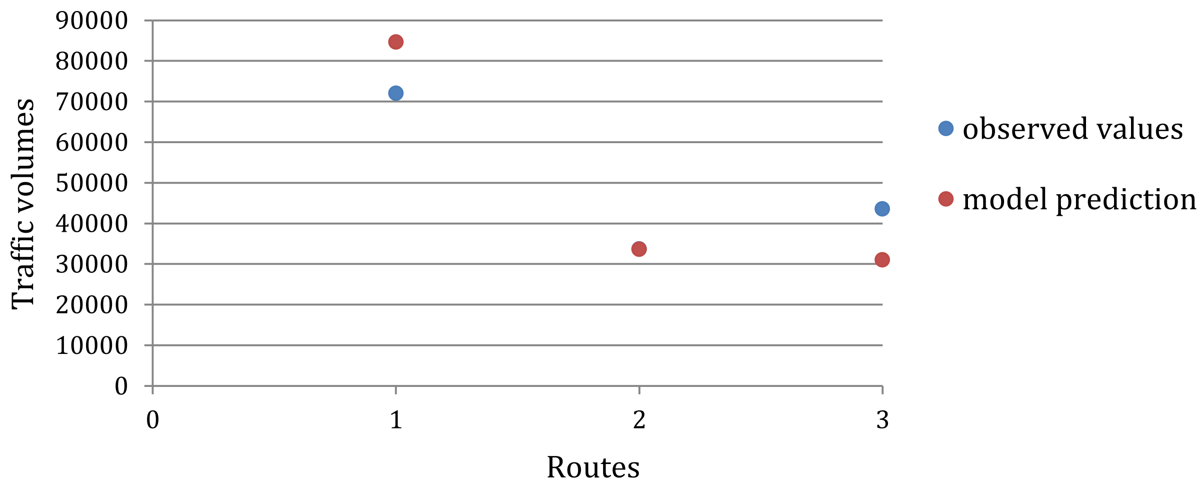

Figure 5.1 Predicted and observed traffic volumes on routes 1, 2, and 3

5.2. Conclusions

According to the final model reported in Table 5.5, there are various variables that affect evacuation route choice. These values include accessibility, facility class, length and perceived service availability. Evacuees prefer to select routes which are more familiar to them, more accessible to them, and have more service available to them. Evacuees also significantly prefer to select freeways over other highways. The fact that these attributes of routes are significant, confirms the first hypothesis of this research.

According to the result of likelihood ratio test that compared values of parameters for first and second time interval, it was concluded that parameters of the model do not generally change as the storm approaches. However, although the model parameters do not show significant overall difference between risk averse and risk tolerant evacuees, individual comparison of parameters show some significance differences and some trends could be detected in the parameter values. As shown in Table (5.7) statistical comparison of parameters of T_1 and T_2 show that coefficients of perceived service, accessibility, and distance are significantly different for risk averse and risk tolerant evacuees. Especially the coefficient of perceived service shows a significant difference between two time periods. Parameter values also suggest that as the storm approaches, people are more willing to take freeways rather than arterial routes. Regarding the trends, as the storm approaches, the length (distance) of routes becomes less important. On the other hand, perceived service becomes more important. These may indicate that as the storm gets closer, people become less discriminating about route features and just want to get out of the area. Expecting more congestion as the storm gets closer, the uncertainty of travel time resulting from congestion would make the availability of service facilities more important.

Table 5.7 Statistical Comparison of model parameters in T1 and T2

Variable	β in T_1	β in T_2	t statistic
Accessibility	-0.042	-0.049	5.32
Distance	-0.011	-0.010	-2.21
Pservice	1.08×10^{-4}	1.71×10^{-4}	-15.08
Facility Class	-0.957	-0.988	0.90

Failing to reject the null hypothesis $\boldsymbol{\beta}_1=\boldsymbol{\beta}_2$ may be due to the long time intervals represented by T1 and T2 which aggregate all the different route choice behaviors. Also, the change in parameter values may occur at a different time interval than the one chosen to separate T1 and T2. Should data be available, running the same model with shorter time intervals, or different time intervals, may better reflect the dynamics of evacuation route choice behavior.

The pure effect of facility class on traffic share of a route is equal to e^{β_3} which is equal to 0.36. Hence, all attributes being the same, if a route is a freeway, it will attract 36 percent more evacuation traffic than if it were an arterial.

AADT was used as the metric for familiarity. Values of AADT included through traffic which could be considered as traffic that will not be involved in evacuation. This results in an inflated familiarity calculation for freeways such as the I-10 and I-12 as through traffic is more likely to use them rather than arterials. Consequently, the model may overestimate the evacuation traffic share on interstate highways.

5.2.1. Elasticity

Accessibility, distance, and facility class of routes are not subject to change on a certain road so discussion on elasticity is confined to perceived service. Equations 5.12 through

5.15 show the calculations on how percentage change in service and familiarity makes changes in perceived service.

$$\text{pservice} = \text{familiarity} \times \text{service} \tag{5.12}$$

$$\Delta\text{pservice} = \text{familiarity} \times \Delta\text{service} + \text{service} \times \Delta\text{familiarity} + \Delta\text{service} \times \Delta\text{familiarity} \tag{5.13}$$

$$\frac{\Delta\text{pservice}}{\text{pservice}} = \frac{\text{familiarity} \times \Delta\text{service}}{\text{pservice}} + \frac{\text{service} \times \Delta\text{familiarity}}{\text{pservice}} + \frac{\Delta\text{service} \times \Delta\text{familiarity}}{\text{pservice}} \tag{5.14}$$

$$\frac{\Delta\text{pservice}}{\text{pservice}} = \frac{\Delta\text{service}}{\text{service}} + \frac{\Delta\text{familiarity}}{\text{familiarity}} + \frac{\Delta\text{service} \times \Delta\text{familiarity}}{\text{pservice}} \tag{5.15}$$

Table 5.8 shows the direct and cross elasticities of traffic shares with respect to route service calculated using formulae derived in section 4.5. Equation 5.15 shows that if familiarity is constant, one percent change in service results in one percent change in the perceived service. This is because the second and third terms in the right hand side of the equation become zero. Similarly, if service is constant, one percent change in familiarity results in one percent change in perceived service. However, a one percent change in the same direction in both familiarity and service, results in more than two percent change in perceived service. Change in opposite directions reduces the impact to below that of the individual factors.

Table 5.8 Elasticites of probabilities with respect to service

	Route 1	Route 2	Route 3
Service 1	0.68	-0.96	-0.96
Service 2	-0.15	0.59	-0.15
Service 3	-0.34	-0.34	1.28

It is noteworthy that cross elastictiesof traffic share of any two routes with respect to service in the other route are equal. For example cross elasticity of routes 2 and 3 with respect to service on route 1 are both equal to -0.96 which means that one percent of incremental change in the service on route 1 would result in 0.96 percent decrease in traffic share of route 2 and route 3. Equality of the cross elasticties, is a product of the independence from irrelevant alternatives (IIA) which is a feature of logit models when alternatives and individuals are independent. IIA states that the odds ratio of selecting any two alternatives is only a function of the attributes of those two alternatives and independent of existence, number, and attributes of any other alternative.

Values reported in Table 5.7 are also valid for familiarity provided that change in familiarity does not change the service availability of a road. This would make the first and third terms in the right hand side of Equation 5.15 equal to zero.

5.3. Future Research

Based on the process and results of this research, a few suggestions to extend the research described in this dissertation are explained in the following paragraphs:

- The route choice model calibrated in this study can be combined with a network loading model to establish a DTA process sensitive to evacuation route choice factors.
- Contraflow is a policy adopted to increase the capacity of routes going outward from the danger area. The model derived in this research is not sensitive to contraflow and calibrating a route choice model with ability to predict the effect of contraflow would make a contribution to the state of the art.
- The current model shows route choice behavior for two time intervals each with approximate length of more than three days. Should data be available, calibrating models on shorter or different time intervals would yield a better understanding of the dynamic of evacuation route choice behavior.
- The issue of transferability of route choice models could be addressed if route choice data were available from various geographical regions.
- The AADT used in the current model is calculated based on the traffic volumes on the routes regardless of their origin and destination. As a result, through traffic is also included in the AADT. This may have inflated the familiarity of interstate highways. Calculating AADT based on traffic going out from New Orleans or at least in-state traffic may result in a more accurate assessment of route familiarity.
- Assessing the effect of socio-economic status of evacuees on their route choice behavior can be useful in predicting the route choice behaviors of neighborhoods.

This can be achieved by running a similar route choice model over variables such as household income, household population, and number of children under 17.

- The logit model used in this study can be replaced with a different version of Logit such as C-Logit to accommodate the dependencies that may exist among alternative routes.

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Appendix

Table A.1 Results of alternatively specified models estimated on data from time period T1

	β	σ	t	p	n	N	LL
ACCESSIBILITY	-0.03	0.01	-3.91	0.00	1	169	-178.8
DISTANCE	-0.01	0.00	-3.73	0.00	1	169	-179.7
FCLASS	-1.39	0.26	-5.27	0.00	1	169	-169.8
SERVICE	1.33E-05	1.4E-05	0.98	0.33	1	169	-187.0
PService	0.0002	3.1E-05	5.18	0	1	169	-173.9
FAMILIARITY	2.99E-06	2.1E-06	1.46	0.15	1	169	-186.4
ACCESSIBILITY	-0.04	0.01	-3.79	0.00	2	169	-161.5
FCLASS	-1.40	0.27	-5.20	0.00			
DISTANCE	-0.01	0.00	-3.68	0.00	2	169	-162.4
FCLASS	-1.37	0.26	-5.22	0.00			
ACCESSIBILITY	-0.04	0.01	-3.72	0.00	3	169	-154.7
DISTANCE	-0.01	0.00	-3.52	0.00			
FCLASS	-1.37	0.27	-5.11	0.00			
ACCESSIBILITY	-0.04	0.01	-3.67	0.00	4	169	-154.7
DISTANCE	-0.01	0.00	-3.49	0.00			
FCLASS	-1.37	0.27	-5.10	0.00			
SERVICE	0.000001	0.00	0.07	0.94			
ACCESSIBILITY	-0.05	0.01	-4.52	0	4	169	-146.2
DISTANCE	-0.01	0.00	-2.83	0.005			
SAFETY	0.05	0.01	4.17	0			
PService	0.0002	0.00	6.06	0			

Table A.2 Results of alternatively specified models on data from time period T2

	β	σ	t	p	n	N	LL
ACCESSIBILITY	-0.04	0.01	-4.3	0.00	1	179	-189.2
DISTANCE	-0.01	0.00	-4.3	0.00	1	179	-189.4
FCLASS	-1.67	0.27	-6.1	0.00	1	179	-174.1
SERVICE	0.00005	1.78E-05	2.6	0.01	1	179	-194.9
PService	0.0002	3.0E-05	6.7	0.00	1	179	-176.2
FAMILIARITY	0.00001	3.0E-06	2.5	0.01	1	179	-195.3
ACCESSIBILITY	-0.05	0.01	-4.4	0.00	2	179	-162.6
FCLASS	-1.76	0.29	-6.1	0.00			
DISTANCE	-0.01	0.00	-4.3	0.00	2	179	-163.5
FCLASS	-1.67	0.27	-6.1	0.00			
ACCESSIBILITY	-0.04	0.01	-3.4	0.00	3	179	-157.3
DISTANCE	-0.01	0.00	-3.2	0.00			
FCLASS	-1.68	0.28	-6.0	0.00			
ACCESSIBILITY	-0.04	0.01	-3.1	0.00	4	179	-156.4
DISTANCE	-0.01	0.00	-3.1	0.00			
FCLASS	-1.64	0.28	-5.8	0.00			
SERVICE	0.00002	0.00	1.4	0.16			
ACCESSIBILITY	-0.05	0.01	-4.4	0	4	179	-143.9
DISTANCE	-0.01	0.00	-2.1	0.03			
SAFETY	0.04	0.01	3.7	0			
PService	0.0003	0.00	7.6	0.00			

Table A.3 Results of alternatively specified model with pooled data

	β	σ	t	p	n	N	LL
ACCESSIBILITY	-0.04	0.01	-5.8	0.00	1	348	-368.0
DISTANCE	-0.01	0.00	-5.7	0.00	1	348	-369.1
FCLASS	-1.53	0.19	-8.1	0.00	1	348	-344.2
SERVICE	0.00	0.00	2.8	0.01	1	348	-383.2
PService	0.00	0.00	8.5	0.00	1	348	-350.6
FAMILIARITY	0.00	0.00	2.9	0.00	1	348	-382.5
ACCESSIBILITY	-0.05	0.01	-5.8	0.00	2	348	-324.7
FCLASS	-1.58	0.20	-8.0	0.00			
DISTANCE	-0.01	0.00	-5.7	0.00	2	348	-326.3
FCLASS	-1.52	0.19	-8.0	0.00			
ACCESSIBILITY	-0.04	0.01	-5.1	0.00	3	348	-312.3
DISTANCE	-0.01	0.00	-4.8	0.00			
FCLASS	-1.53	0.19	-7.9	0.00			
ACCESSIBILITY	-0.06	0.02	-2.7	0.01	4	348	-119.2
DISTANCE	-0.02	0.01	-2.8	0.00			
FCLASS	-0.73	0.27	-2.7	0.01			
SERVICE	0.00001	0.00	0.4	0.66			
ACCESSIBILITY	-0.05	0.01	-6.3	0	4	348	-290.7
DISTANCE	-0.01	0.00	-3.5	0.00			
SAFETY	0.05	0.01	5.7	0			
PService	0.0002	0.00	9.7	0			

Vita

Meisam Akbarzadeh was born in the city of Kerman, Iran in September 1979 to Hadi Akbarzadeh and Fatemeh Aghdaei. He received his Bachelor of Science degree in Electrical Engineering in 2002 and a Master of Science degree in Industrial Engineering in 2007 from Isfahan University of Technology. He also earned a Master of Science degree in Civil Engineering from Louisiana State University in 2009. He will receive his Doctorate degree in Civil Engineering from Louisiana State University in 2012. Meisam lives with his wife Houry and his daughter Fatima.